

**HEC MONTRÉAL**

**Green Discounts and Greenwashing  
in the U.S. Corporate Market**

par

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# Résumé

Ce mémoire étudie l'existence d'une sous-valorisation des obligations vertes sur le marché américain des obligations d'entreprise, et analyse les facteurs déterminant le comportement de greenwashing au niveau des entreprises. À partir d'un ensemble de données composé de 409 obligations vertes émises par 146 entreprises américaines entre 2013 et début 2025, l'étude combine des données de tarification au niveau des obligations avec des indicateurs de performance et de divulgation ESG des entreprises, afin de mesurer l'écart entre les déclarations environnementales et les résultats réels. L'analyse repose sur des régressions en moindres carrés ordinaires (OLS), avec des erreurs standards robustes et groupées, en contrôlant les fondamentaux des entreprises ainsi que les effets fixes. Les résultats montrent que les obligations vertes sont généralement sous-valorisées par rapport à leur coût de la dette calculée à partir du WACC, ce qui est cohérent avec des études antérieures suggérant un coût de financement plus élevé pour les instruments durables. Par ailleurs, le comportement de greenwashing est influencé par des caractéristiques propres aux entreprises, telles que la qualité de crédit, la gouvernance et le sentiment des investisseurs. Des tests de robustesse, incluant différentes mesures de greenwashing, le regroupement des erreurs et des tests de causalité inversée, confirment que les résultats ne sont pas liés à une mauvaise spécification du modèle. Au final, cette étude met en lumière que, bien que le marché américain des obligations vertes ait connu une forte croissance, la tarification reflète à la fois une volonté d'encourager la durabilité et un certain scepticisme quant à la crédibilité des engagements environnementaux. Ces résultats contribuent à une meilleure compréhension des interactions entre la qualité du reporting ESG, le greenwashing et la finance durable.

**Mots clés:** *obligations vertes, green discount, greenium, greenwashing, ESG, finance durable, finance d'entreprise*

# Abstract

This thesis examines the existence of a “green discount” in the US corporate bond market and explores the determinants of the firm-level greenwashing behavior. Using a dataset of 409 green bonds issued by 146 US corporations between 2013 and early 2025, the study combines bond-level pricing data with firm-level ESG disclosure and performance metrics to quantify the divergence between environmental claims and actual outcomes. The analysis employs ordinary least squares regressions with robust and clustered standard errors, controlling for firm fundamentals and fixed effects. Results show that green bonds are priced at a discount relative to their WACC-based cost-of-debt, consistent with prior evidence on higher financing costs for sustainable instruments. Additionally, greenwashing behavior is shaped by firm-specific characteristics like credit quality, governance score, and investor sentiment. Robustness checks using alternative greenwashing measures, clustered errors, and reverse-causality tests confirm that findings are not driven by model specification. Overall, the study highlights that while the U.S. corporate green bond market has expanded significantly, investor pricing reflects not only sustainability signaling but also skepticism toward credibility. These results contribute to understanding the intersection of ESG reporting quality, greenwashing, and sustainable finance.

**Keywords:** *Green Bond, Green Discount, Greenium, Greenwashing, ESG, Sustainable Finance, Corporate Finance*

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# List of Abbreviations

| Abbreviation | Full Term                                       |
|--------------|-------------------------------------------------|
| ESG          | Environment, Social, Governance                 |
| GD           | Green Discount                                  |
| GW           | Greenwashing                                    |
| GWScore      | Greenwashing Score                              |
| IFRS         | International Financial Reporting Standards     |
| ISSB         | International Sustainability Standards Board    |
| NAIC         | National Association of Insurance Commissioners |
| OLS          | Ordinary Least Squares                          |
| SDGs         | Sustainable Development Goals                   |
| SEC          | Securities and Exchange Commission              |
| SPOs         | Second party opinions                           |
| S&P          | Standard & Poor's                               |
| WACC         | Weighted Average Cost of Capital                |
| YTM          | Yield to Maturity                               |

# 1. Introduction

## 1.1 Motivation: Sustainability is on the Global Radar

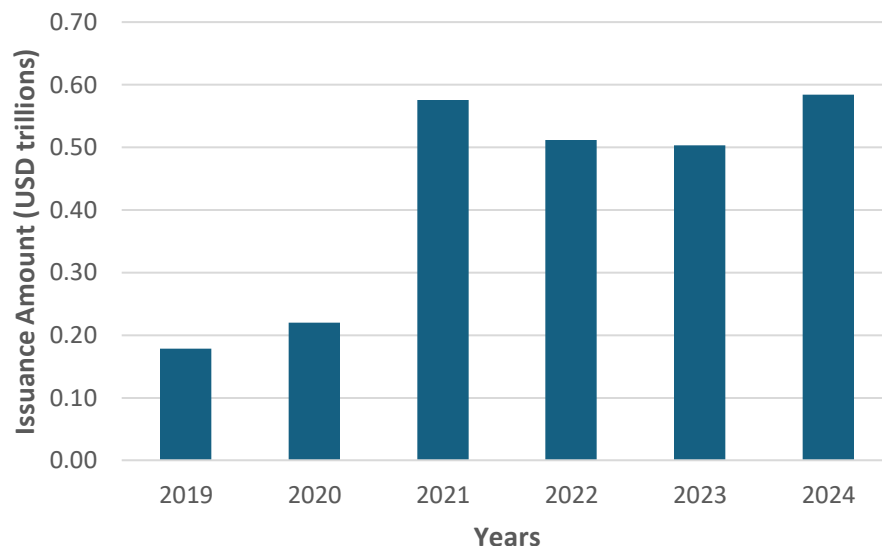
In the past decade, sustainability has ascended as one of the core priorities in economic policy and financial strategy around the world. Accelerating climate change, biodiversity loss, and environmental degradation are forcing policymakers, regulators, and investors to reevaluate the long-term risks and externalities embedded in business models. The global community has also come together to commit to a low-carbon sustainable future through the Paris Agreement 2015, the UN Sustainable Development Goals (SDGs), and multiple national climate action plans.

As policy momentum and public awareness increase, so too are financial markets adapting. Investors and institutions have increasingly started to consider incorporating the environment, social, and governance (ESG) factors into their investment decision-making process. To react to this demand, the financial market has created instruments that channel money directly into environmental goals. Among them, the debt market is a natural “focal point”, because bonds are the core of pension-funds and insurance portfolios to guarantee long-term stable capital gains. Adding ESG factors to fixed-income allows investors to enjoy the benefit of low-volatility capital appreciation, at the same time, align with environmental prospects; this is a unique advantage of bonds that equity cannot offer. The rapid rise of labeled securities, such as green and sustainability-linked bonds is therefore pushing the “ESG-thinking” into “one of the fastest-growing corners of finance” (IFC, 2023). In the global fixed-income market, sustainable bond issuance reached a record-high of US\$1 trillion in 2024 - a 20% increase from the previous year. Green bonds still dominated the total issuance, with nearly 58% (ICE, 2025).

Green bonds are fixed-income instruments that are used to fund projects with environmental and climate purposes, such as renewable energy, energy efficiency, and

sustainable infrastructure. Figure 1 shows the rise in green bond issuance. Since its inception in 2017, there has been substantial growth; and in 2024, the issuance reached a record high of \$571 billion (Lee, 2025). Region-wise, Europe is the biggest issuer of green bonds, accounting for more than 50% of the sales; this is followed by Asia (led by China, 27.2%) and then North America (13.3%) (ICE, 2025; Lee, 2025). Corporations are the main issuers of green bonds (CBI, 2025). Other issuers include sovereign governments, municipalities and subnational entities, and supranational institutions.

**Figure 1: Annual Green Bond Issuance, 2019 - 2024**



*Figure 1.* This figure presents annual issuance volumes of green bonds calculated by the author using data from the Climate Bonds Initiative (2025).

## **1.2 Overview of the US Green Bond Corporate Market**

The US issued its first green bond in June 2013, by the Commonwealth of Massachusetts. From there, the market has surged, particularly with municipal issuers. As of November 2024, total sales of green bonds hit USD \$550 billion, approaching the previous peak of \$588 billion in 2021 (Bloomberg, 2024). However, this growth occurred within a

regulatory and market context that is different from other major green bond markets, setting a stage for a closer examination of its unique nature.

The US market provides a relatively looser environment for green bond issuance, compared with Europe and China. First, the country lacks universally recognized system for determining what qualifies as a green bond, in contrast to the EU Green Bond Standard or China's state-led policy and regulatory mandates (Fatica et al., 2021). In the US, issuers may self-label, rely on second party opinions (SPOs), or be classified by data providers like Bloomberg. For example, the US Securities and Exchange Commission (SEC) March 2024 climate-disclosure rule, which is now on hold, would have obliged firms to report their own greenhouse-gas emissions, yet it offered no test for what counts as a green bond and did not require an external opinion. As a result, many US corporates issue labelled bonds without an SPO. Due to such divergent label standards, the US investors face inconsistent information.

Additionally, because the ESG-related disclosures in the US are voluntary and the issuers have choices to claim to be green, the low bar cuts the cost of claiming greenness and increases incentive to “greenwash”: the misrepresentation or exaggeration of a firm's environmental commitments on the true impact of its sustainability-labeled products. Although SPOs from providers like S&P Global and Morningstar | Sustainalytics can boost credibility, the International Capital Market Association barely recommends such reviews, yet no US statute or SEC rule makes them mandatory. Many firms skip them to save time and fees, even though they know that some ESG-focused investors may demand a premium for it or avoid the deal completely. Such behaviour creates pricing uncertainty and potential risk for investors, especially in the corporate bond market where disclosure discretion is higher than in sovereign or supranational issuances. As a result, investors would question the credibility of green bonds, they would pressure for transparency and clearer disclosure (Fatica et al., 2021).

As noted earlier, the relatively high legal flexibility provides companies with opportunities greenwash. Greenwashing in green bonds happens when issuers deceptively materialize on the “green” label to attract ESG-oriented capital. Misleading strategic disclosure, insufficient transparency, or reliance on weak or voluntary certification standards - such behaviors make it difficult for investors to verify the credibility of environmental claims. For example, Mighty Earth, a non-governmental organization, filed SEC complaint against JBS, because JBS misled investors in a 2021 sustainability-linked bonds issuance that raised \$3.2 billion. The company also failed on its commitment to cut its emissions by 30% by 2040 and eliminate illegal deforestation from its supply chain by 2025 (Webzel, 2023). These issues have made investors and regulators question whether green bonds genuinely offer environmental value or whether they are just marketing tactics.

Moreover, very little academic literature exists on the US corporate bond market remains, despite the size and importance in the global market (Zhang et al., 2022). Current studies often focus either on European issuers who benefit from more standardized disclosures or on the US municipal bond market which is generally lower-risk and more transparent. Recent work also emphasizes this gap: Kim (2025) counts barely 332 issues in the US corporate market from 2015 to 2024 and calls the evidence base “still evolving”. A survey by Flottmann et al. (2025) finds that most US research still centres on municipal, not corporate, debt. The gap persists because the market is still immature and small with restricted data access, disclosures lack common template, and issuers span in credit grades and sectors, conditions that make large and clean samples hard to construct and compare. With the combination of regulatory discretion and limited scholarly interest, the US corporate green bond market offers an ideal case for in-depth study.

### **1.3 Research Questions**

One important phenomenon in the green bond market is the pricing differential between green and conventional bonds. It is commonly referred to as the “greenium”: a premium

embedded in a green bond. It reflects investors' willingness to accept reduced yields in exchange for environmental impact. Inversely, in some cases, a green discount (GD) exists, where green bonds trade at higher yields and it reflects the market demand for the risks or uncertainties associated with funding sustainable projects, possibly due to higher risks such as credit risk, longer duration, low liquidity, also reflecting investor skepticism over "greenwashing".

Empirical work yields no consensus on whether green bonds price better or worse than conventional debt. Some studies identify modest premium: a 6 basis points after-tax greenium for U.S municipals (Baker et al., 2018) and 15 - 24 basis points in a global corporate sample (Löffler et al., 2021). Others report no significant difference: US corporate or municipal issues are identical to their conventional matches (Lam & Wurgler, 2024; Larcker & Watts, 2020; Shannon et al., 2025). And in one study green bonds are reported a 23 basis points discount relative to their brown counterparts (Karpf & Hahn, 2017). Because only a handful of papers focus squarely on US corporates, the direction and size of any pricing gap in this market remain unresolved.

Given the mixed empirical evidence across different regions, time periods, and market types - including both primary and secondary market transactions, it remains unclear whether a consistent greenium or green discount exists in the US, particularly within the corporate bond sector. These inconsistencies raise important questions about the underlying drivers of green bond pricing. This motivates the thesis to question, in the corporate world,

- *Is there a greenium or a green discount? Could part of it be attributed to greenwashing?*

*And*

- *What firms are more likely to engage in greenwashing?*

This thesis investigates these objectives with a hand-built panel of all US-domiciled corporate green bonds issued from 2013 through 2025. Each issue is matched to the issuer's firm-specific cost-of-debt. The yield-spread calculation is used to quantify the price gap; and panel regressions are adopted to test the drivers for the bond-level greenium/discount and the firm-level greenwashing behaviour. The findings will clarify how various bond-and-firm level factors shape the yield for US companies that issue green bonds.

#### **1.4 Contribution**

Methodologically, the study contributes to the literature by introducing a Weighted-Average-Cost-of-Capital (WACC)-based yield benchmark for detecting yield differences as an alternative to the dominant matching approach. A comprehensive discussion comparing the two methods is provided in Section 2.3. Unlike the predominant matching approach which compares green bonds with paired conventional counterparts, the WACC-based framework compares each bond's expected yield from its issuer's specific after-tax cost of debt. The matching principle is inherently limited in markets, especially the US corporate green bond market, where suitable non-green matches are scarce or entirely absent for many issuers, even though it remains valuable for isolating treatment effects under tightly controlled bond characteristics. The WACC-based design avoids such sample restrictions and matching bias. Moreover, it provides a theoretically grounded measure of expected yield that incorporates firm-specific financing costs, this approach offers a more direct approach to evaluate how market participants price environmental attributes in the corporate bond market. This unique framework thus offers a more flexible and theoretically consistent means of identifying pricing effects linked to green bond issuance.

Second, this paper distinguishes itself by examining both bond-level and firm-level dimensions as two complementary components. This approach bridges market microstructure effects (e.g., liquidity, duration, credit quality) and organizational

sustainability practices (e.g., ESG pillar performance, governance strategy, investor sentiment). At the bond level, this study investigates how security-specific characteristics, such as market demand, bond features, and credit quality, affect the pricing of green bonds, controlling for industry and year fixed effects. At the firm level, it explores how issuer-specific attributes, including disaggregated ESG pillar scores, investor sentiment, and firm fundamentals, are associated with greenwashing behavior, thereby capturing the broader organizational and market context. Linking these two perspectives therefore enables this paper to trace potential channels through which the firm-level sustainability behaviour may influence bond-level pricing outcomes. In doing so, this study moves beyond the isolated analyses of either bond characteristics or corporate sustainability profiles, it provides a more complete picture of the interaction between ESG practices, market credibility, and the cost of capital in the US corporate bond market.

Within the bond-level analysis, this paper also incorporates duration as a bond feature used as a standard control variable. Preliminary observations (presented in Section 5.2.1) indicate that green bonds in the sample tend to have longer maturities, this suggests that they are generally more sensitive to interest rate fluctuations and may influence investor perception of credit risk; duration therefore may play a meaningful role in presenting such pricing dynamics. Since green bonds are typically long-term instruments, it is useful to test if maturity-related risk exposure influences their pricing.

On the firm side, the paper distinguishably disaggregates the overall ESG performance score into its three separate pillars: Environmental (E), Social (S), and Governance (G), to examine their distinct relationships with greenwashing behavior. Although the aggregated ESG scores are widely used, it may miss the offsetting effects between pillars. This pillar-level approach reduces such overlapping risks and helps assess which ESG dimensions are most closely associated with greenwashing behavior. Thus, analyzing the pillars separately helps provide a more detailed perspective that can reveal whether, for example, environmental underperformance is a stronger indicator of potential

greenwashing than social or governance shortcomings. Such disaggregation not only contributes to the relatively limited pillar-level research in the academic literature but also provides practical relevance for investors, analysts, and regulators seeking to identify ESG constitution specification.

Lastly, this paper provides an updated empirical assessment of the US corporate green bond market using a dataset that extends through 2025. This extended coverage captures post-pandemic market dynamics and sets the analysis in the context of the ongoing debates over climate policy and ESG disclosures, and sustainable investment strategies. The study reflects the most recent market conditions and regulatory developments, offering a timely perspective on emerging trends and evolving risks in the sustainable debt market.

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on the pricing of green bonds, the effect on demand in the market, and greenwashing. The dependent variables are defined, and the main and sub-hypotheses are presented in Sections 3 and 4, while Section 5 describes the dataset and presents descriptive statistics. The empirical model framework and estimation approach is presented in Section 6, along with fixed effects specification and variable construction. In Section 7, the regression results are reported and interpreted in relation to the hypotheses. Section 8 identifies the limitations of the study. Finally, Section 9 wraps it all up by summarizing all the important contributions which are useful for sustainable finance.

## **2. Literature Review**

### **2.1 Empirical Evidence on the Greenium: Global vs. US Markets**

Empirical studies report mixed evidence on the existence and magnitude of the green “difference”. Table 1 summarizes 15 studies of green-bond pricing published since

2018. Global and European corporate samples report a modest greenium of 2 - 5 basis points (Pietsch & Salakhova, 2022; Zerbib, 2018); early US municipal work ranges from +6 basis points after-tax (Baker et al., 2018) to -23 basis points (Karpf & Hahn, 2017). The most stringent “twin-bond” designs find little to no premium: Larcker and Watts (2020) show that 86 % of matched US municipal bond pairs carry identical yields, and Flammer (2021) reports an average discount of 1.9 basis points for US corporates - statistically zero. Recent panels that extend the window to 2024: Kim (2025) and Shannon et al. (2025) confirm a flat or slight discount. With the mixed and inconclusive results, research specifically focused on the US corporate green bond market is still limited and the evidence of greenium is fragile, despite its significant role in the global green bond landscape.

One explanation of the finding divergence could be the region and the market. Columns (2) and (3) in Table 1 show a clear pattern: sovereign, supranational, and municipal bonds in global samples often price at a small premium; but this effect shrinks, and sometimes even becomes negative once the focus narrows to the US corporates. Several US-specific characteristics can help explain this shift. First, as explained in section 1.2, loose label rules and optional SPOs leave investors uncertain about whether proceeds will be used as promised, so they ask for extra yield. Second, bondholders, as senior claimants, do not share the full upside ESG gains - the better ESG performance is primarily captured by shareholders, this discourages the bondholders from paying a premium (Flammer, 2021). Third, underwriting fees for green tranches run about 10 % higher, it offsets any pricing benefit (Larcker & Watts, 2020). Fourth, the perceived greenwashing risk adds another source of uncertainty, this could further widen the yield. Finally, US green issuance is concentrated in utility and heavy-industry credits that already trade wide; if matching is not perfect, this sector bias pulls average spreads above vanilla debt. After risk, tenor, and liquidity are equalized, labelled and plain-vanilla US corporate debt look like near substitutes, and any residual price gap must arise from channels other than cheaper borrowing - a proposition tested in the sections that follow.

Another explanation for the result divergence could be the methodological choices, as shown in Column (6) in Table 1. Matched-pair OLS designs like in Zerbib (2018) search the market for the closest vanilla twin by rating, tenor, and currency, because the two bonds still differ on issue date or liquidity, any residual mismatch can leak into the estimated spread. Exact-twin studies, Flammer (2021); Larcker and Watts (2020), remove that noise by requiring the green and conventional groups to be sold by the same issuer on the same day, this way immediately reduces uncontrolled variation; with it, the apparent greenium decreased or even became negative. Event-study frameworks by Schneider (2024) sidestep yield levels altogether and track abnormal returns around announcement dates; they can capture short-lived demand surges that vanish once the bond settles into secondary trading. Heterogeneous panel regressions (Kim, 2025) dispense with hand-matching and instead average thousands of bonds with issuer or time fixed effects; this improves sample size, but mixes securities issued under very different market conditions, this dilutes a small pricing signal. In short, the stricter the alignment of risk, timing and liquidity factors, the less room remains for a standalone greenium to appear, thus the more likely the green discount is.

The next subsection reviews those channels in detail, tracing how investor preferences, signaling incentives, liquidity frictions, and climate-risk concerns can each widen or compress labelled-bond spreads even after conventional risk factors are matched.

| (1)<br>Study & Year          | (2)<br>Region | (3)<br>Issuer type                            | (4)<br>Sample period | (5)<br>Sample size                 | (6)<br>Method             | (7)<br>Reported greenium (bps)                             |
|------------------------------|---------------|-----------------------------------------------|----------------------|------------------------------------|---------------------------|------------------------------------------------------------|
| Zerbib 2018                  | Global        | Corporates                                    | 2013-2017            | 135 matched pairs                  | Matched pair, OLS         | 2-5                                                        |
| Zerbib 2019                  | Global        | Corporates                                    | 2014-2018            | 206 matched pairs                  | Liquidity-adjusted panel  | 2                                                          |
| Bachelet et al. 2019         | Global        | Corporates                                    | 2013-2017            | 89 matched pairs                   | Matched pair              | 1-2 for institutions, -2- -12 for private issuers          |
| Löffler et al. 2021          | Global        | Large corporates, sovereigns                  | 2015-2020            | 310 bonds                          | Propensity score          | 15 - 24                                                    |
| Fatica et al. 2021           | Global        | Primary markets: supranational and corporates | 2007-2018            | 1397 green vs. 270000 conventional | OLS, FE                   | 80 supranations; 22 non-financial corporates; 0 financials |
| Kapraun et al. 2021          | Global        | Primary and secondary                         | 2009-2020            | 1500 green vs. 20000 conventional  | Matched pair, panel       | 5-18 for credible bonds                                    |
| Schneider 2025               | Europe & U.S. | Corporates                                    | 2016-2024            | 194 matched pairs                  | Event study               | -7                                                         |
| Pietsch & Salakhova 2022     | Europe        | Corporates                                    | 2016-2021            | 620 matched pairs                  | Matched pair, OLS         | 4                                                          |
| Baker et al. 2018            | U.S.          | Municipals                                    | 2013-2016            | 839 bonds                          | Matched pair, FE          | 5-7, up to 15-26 if certified                              |
| Larcker & Watts 2020         | U.S.          | Municipals                                    | 2013-2018            | 640 matched pairs                  | Exact twin match          | 0 (86% identical)                                          |
| Karpf & Hahn 2017            | U.S.          | Municipals secondary                          | 2014-2016            | 1880 green vs. 34000 brown         | Term-structure comparison | -23                                                        |
| Lam & Wurgler 2024           | U.S.          | Municipals and Corporates                     | 2013-2021            | 1004 matched pairs                 | Matched pair              | 0                                                          |
| Flammer 2021                 | U.S.          | Corporates                                    | 2013-2018            | 195 matched pairs                  | Exact twin match          | -1.9 (stat. 0)                                             |
| Kim 2025                     | U.S.          | Corporates                                    | 2015-2024            | 332 bonds                          | Hetero panel              | -3 -2                                                      |
| Shannon, Gong & Sheehan 2025 | U.S.          | Corporates                                    | 2017-2024            | 259 leaks                          | Pre-issue event           | 0                                                          |

**Table 1: Summary of Empirical Evidence on Greenium**

*Table 1.* This table summarizes 15 empirical studies of green bond pricing published since 2018. Reported values in Column 7 represent estimated yield differentials between green and conventional bonds, expressed in basis points (bps). Positive values indicate a greenium, while negative values indicate a green discount. Reported magnitudes vary by market, issuer type, and methodology.

## **2.2 Economic Drivers of Green Bonds**

Green bonds offer distinct financial and non-financial benefits to both investors and issuers; these benefits help explain their increasing attractiveness.

### **2.2.1 Benefits for Investors**

For investors, green bonds offer enhanced liquidity, and the liquidity profile is as important as its yield. Evidence shows that green-labelled issues often settle into deeper, more active secondary markets than comparable conventional bonds, which allows large blocks to change hands with smaller price concessions. In his global study, Zerbib (2019) documents that once green bonds move from the initial placement phase to routine trading, their bid-ask spreads narrow relative to matched vanilla bonds. Regional work by Febi et al. (2018) finds a similar pattern in Asian markets: the six-month-old green bonds post lower return volatility and faster quote revisions than standard corporate bonds. The US evidence from Bachelet et al. (2019) also agrees with this phenomenon: the turnover of corporate green bonds is 18 percent more frequent than their non-green matches and end their first year with a bid-ask spread 12 percent smaller. More liquid bonds like so enable portfolio managers to rebalance positions and meet redemptions within minimal price slippage - the green bonds are therefore more attractive even if they offer little or no yield premium. Thus, better liquidity offers more than a premium, this explains why large regulation-constrained investors such as institutions and pension funds continue to demand labelled debt.

The other growing benefit of green bonds is hedging against climate risks. Green bonds perform relatively well under rising climate uncertainty, because they may offer protection against physical climate shocks like extreme weather events, sea-level rise, and drought, as well as against transition risks arising from policy changes, regulation or market adjustments associated with the low-carbon transition. These risks can lead to significant financial disruptions, such as asset devaluation, operational interruptions, and higher compliance costs for carbon-intensive companies. Green bonds mitigate such

climate-related risks by directing capital toward projects that intend to improve environmental resilience. Because of this, the risk of regulatory penalties, reputational damage, or shifts in investor preferences away from carbon-intensive investments is low. For institutional investors, it encourages alignment with climate mitigation and adaptation in the portfolio also lowers exposure to both stranded assets and long-term climate-induced volatility.

Green bonds could also be a strategic signal for climate responsiveness for regulators, asset owners, and stakeholders. It is especially true for investors with ESG mandates or fiduciary responsibility to manage long-term systemic risks. Here, issuing green bonds serves two purposes: providing financial protection against climate risk and supporting broader climate-aligned investment frameworks, such as those in the Paris Agreement and net-zero transition pathways. For investors, it helps with risk-adjusted returns and alignment with long-term sustainable goals.

Finally, green bonds can offer their non-financial utility via alignment with the environmental goal. Investor preferences in capital markets are often modeled through utility functions balancing between expected return and risk. For green bonds, this framework extends to non-financial payoffs, such as psychological satisfaction or alignment with personal environmental preferences, which some investors benefit by holding eco-friendly assets. As Baker et al. (2018) find, certain investors gain non-pecuniary utility from green financing; their investment decisions of portfolios are motivated by both risk-adjusted returns and ethical considerations. Just as consumers may pay extra for eco-labeled products, these investors are willing to accept slightly lower yields in exchange for exposure to assets that match their values. This utility-driven behavior explains the pricing differential between green and non-green bonds, highlighting the importance of internal motivation in the growth of sustainable finance.

### 2.2.2 Benefits for Issuers

From the issuer's perspective, green bonds provide a pricing advantage through the greenium. The preference-driven demand, shown as the lower required yield from the investor's side, translates into a lower cost of debt for the issuer. Empirical evidence from Fatica et al. (2021) supports this mechanism, it emphasises that green bond issuers enjoy more favorable pricing due to the enhanced transparency and credibility that they signal to the market, relative to conventional issuers. Green-labeled instruments often come with promises of reporting the use of proceeds, disclosing the environmental impact, and, if they are considered more credible, obtaining third-party verifications like SPOs. All of these can lessen information asymmetry between firms and investors and boost market trust. Thus, the pricing advantage of green bonds expresses the market trust in the issuer's accountability and environmental integrity.

However, such pricing advantage is not automatic. When that credibility is weak or symbolic, the intended benefits may reverse. As explained in sections 1.2 and 2.1, in the absence of rigorous disclosure standards or external assurance, green bonds may amplify information asymmetry and increase the greenwashing risk. Although green bonds have the potential to reduce borrowing costs through transparency and investor utility, their effectiveness depends critically on the strength of verification mechanisms and the issuer's actual environmental commitment.

In addition, green bonds can grant access to a growing pool of ESG-focused capital. Demand for sustainable investing has increased, institutional investors like pension funds, insurance companies, and mutual funds have also accordingly incorporated ESG criteria into their investment screening. This trend has created a unique segment in the capital market for environmental finance. Firms can signal sustainability through green bond issuance, therefore, becoming eligible for inclusion in this segment and attracting capital unavailable through traditional debt. When they have more access to capital, their financing flexibility, especially over the long term will be improved as well. ESG-focused

investors typically have longer time horizons, they like to maintain stable holdings, so they can offer a more reliable capital reliable than traditional market participants. Larcker and Watts (2020) indicate that green bonds diversify the investor base by drawing sustainability-driven and long-horizon investors. This diversification not only enhances the issuer's resilience during market uncertainty but also strengthens its position in a financial environment that is increasingly shaped by climate and sustainability imperatives.

Beyond financial advantages, green bond issuance also brings non-financial values to the company. A key benefit is its role as a strategic signaling tool. As Hu et al. (2024) finds, green bonds can serve as an effectively indicator of a firm's environmental commitment, helping to reduce information asymmetry with investors. This signaling function is crucial in markets where standardized green taxonomies are still developing like the US corporate market, because investors perceive these sustainability claims as legitimate and authentic (Flammer, 2021). Besides, the empirical proof from the same study shows that green bond issuance improves firms' environmental performance and increases ESG-sensitive institutional ownership (Flammer, 2021). This also implies that green bonds can help align a firm's investors with long-term sustainability goals. Further, in sustainability-focused institutions, according to Löffler et al. (2021), green bonds contribute positively to corporate legitimacy and brand positioning. Overall, the broader strategic value of green bonds are: financing environmental projects as well as enhancing a firm's credibility, stakeholder alignment, and long-term positioning in a sustainability-oriented market.

### **2.3 Methodological Approaches: The Matching Principle vs. WACC-based Cost of Debt**

The matching principle, introduced by Zerbib (2018), is a widely used methodological approach in green bond research to assess the existence of greenium. The method was inspired by empirical asset pricing and credit risk research trying to isolate the effect of a single variable by holding other factors constant. The idea is to compare each labelled

bond with the closest conventional (non-green) twin on all observable risk characteristics: issuer, currency, seniority, rating, collateral, and coupon type, so that any remaining spread reflects the green label itself. This method has since become a benchmark mythology that is broadly used in subsequent studies. For example, Baker et al. (2018) matched pairs of green and non-green bonds issued by the same entity on the same day of US municipal bonds, adding issuer fixed effects and tax status. Larcker and Watts (2020) and Flammer (2021) tighten this method further by requiring the green and non-green tranches be sold by the same issuer on the same day. Related studies, such as Zerbib (2019) and Karpf & Hahn (2017) extend the same approach with propensity-score and synthetic-control matches to cover larger global samples. In addition, across these studies, the control set is consistent: coupon rate, maturity, face value, and modified duration. This method is popular because it neutralises observable bond-level risk factors while preserving market pricing.

Despite its popularity, such design inherits several limitations. First, it is extremely difficult to find a “perfect” match for a green bond: after filtering for all the bond characters, many green bonds have no suitable twin - this eliminates most observations (a matching method is conducted in section 7.3 to test the sample in this paper to address this issue). For example, in Zerbib (2018), 955 of the original 1065 were dropped out, only 110 matched green bonds were used in his global study - this could be worse for the US corporate market since the sample base is even smaller. Second, even the closest “twin” can differ in other features that matter for pricing, such as liquidity, call provisions, and covenant packages, it is not safe to conclude the yield difference is solely due to the “greenness”, rather than such heterogeneity noises. Last, human errors could happen. As most studies manually pick matches or with ad-hoc screens, small changes in the rules can shift the result dramatically, introducing measurement error and potential bias. These drawbacks show that although matching helps control observable risk factors, it cannot fully eliminate selection bias or unobserved variation in the green bond pricing.

To avoid these pitfalls, the matching method is replaced with an issuer-specific cost of debt,  $R_d^{WACC}$ , derived from the WACC formula<sup>1</sup> while keeping the standard bond level characteristic controls. Because  $R_d^{WACC}$  is directly calculated from the firm's entire debt stack, it already embeds the bond structure and the tax status that shape the pricing. Every green bond therefore has an automatic, internally consistent comparator, so no observation will be lost for the lack of suitable match. Because essentially no bond will be eliminated from the database, this can also avoid the small-sample bias, and the expanded data also helps increase modeling accuracy. In addition, since  $R_d^{WACC}$  can be directly obtained from balance sheets or market data, it reduces human error and allows the green yield differential to be computed directly from regression analysis. The WACC-based benchmark thus provides a cleaner, sample-wide measurement of any greenium or green discount in the US corporate market.

## 2.4 Greenwashing Risk

Greenwashing is deceptive statement or practice of a firm's environmental commitment; a gap is created between the firm's green image and its actual performance. This risk is especially acute in the US corporate bond market, where green labels are self-declared, their-party reviews are optional, and the cost of making exaggerated claims is low (see Section 1.2). Because mislabelling can misprice bonds and misallocate capital, understanding and quantifying greenwashing is important to any study of US corporate green bonds - both for investors who demand integrity and for regulators who seek market transparency.

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<sup>1</sup> The Weighted Average Cost of Capital (WACC) represents the average rate a firm must pay to finance its operations,  $WACC = w_d r_d (1 - T_c) + w_e r_e$  Where  $w_d$  and  $w_e$  are the market weights of debt and equity,  $r_d$  is the pre-tax cost of debt,  $T_c$  is the corporate tax rate, and  $r_e$  is the cost of equity.

A common methodology adopted by researchers to access the level of greenwashing is calculating the difference between the reported ESG score and the real ESG score. Here, the reported ESG score is the disclosure score, it reflects how extensively a firm reports on environmental practices; and the real ESG score is the performance score which represents the actual environmental outcomes. Then, the difference between a firm's normalized disclosure score and the normalized performance score is calculated, this difference proxies for the extent of greenwashing. A higher difference indicates a greater degree of greenwashing. For example, Yu et al. (2020) apply this metric to a global sample, arguing that a larger positive gap signals more overstatement of sustainability claims. Lin et al. (2023) use the same disclosure-performance difference for Chinese listed companies, confirming its portability across markets. This study follows an identical approach to measure the degree of greenwashing. Section 4.2 details the standardization of it and Section 5 explains how it's obtained. In addition, as greenwashing is ultimately a firm-level choice, the regression framework also includes firm-specific characteristics such as size, leverage, profitability, and other corporate traits to capture underlying drivers.

### 3. Dependent Variable Explanations

#### 3.1 Estimation of Green Discount

The green discount is defined as the difference between a green bond's observed yield-to-maturity (YTM) and its implied yield derived from the after-tax cost of debt:

$$GD_{i,t} = YTM_{i,t} - R_{d,i,t}^{WACC} \quad (1)$$

Where,

- $GD_{i,t}$  is the green discount of green bond  $i$  at time  $t$ ;
- $YTM_{i,t}$  is the observed yield-to-maturity of that bond at time  $t$ ; and
- $R_{d,i,t}^{WACC}$  is the after-tax cost of debt for that bond, calculated using a WACC-based approach.

A positive  $GD_{i,t}$  indicates that the green bond carries a higher yield than its implied benchmark, suggesting the presence of a green discount. Otherwise, it indicates a greenium.

### 3.2 Estimation of Greenwashing

The greenwashing score ( $GWScore$ ) is defined as the difference between a firm's normalized ESG disclosure score and its normalized ESG performance score:

$$GWScore_{i,t} = \frac{ESG\ disc_{i,t} - \overline{ESG\ disc}_{i,t}}{\sigma_{ESG\ disc,i,t}} - \frac{ESG\ perf_{i,t} - \overline{ESG\ perf}_{i,t}}{\sigma_{ESG\ perf,i,t}} \quad (2)$$

Where,

- $ESG\ disc_{i,t}$  is the ESG disclosure score of firm  $i$  at time  $t$ ;
- $\overline{ESG\ disc}_{i,t}$  is the mean of ESG disclosure scores of all the firms in the sample;
- $\sigma_{ESG\ disc,i,t}$  is the variance of those scores;
- $ESG\ perf_{i,t}$  is the ESG performance score of the same firm and period;
- $\overline{ESG\ perf}_{i,t}$  is the mean of ESG performance scores of all the firms in the sample;
- and
- $\sigma_{ESG\ perf,i,t}$  is the variance of those scores.

A higher  $GWScore_{i,t}$  indicates a greater divergence between what the firm reports and its actual ESG outcomes, suggesting a higher extent of greenwashing.

## 4. Hypothesis Development

### 4.1 Main Hypothesis 1: Existence of Green Discount and its Drivers

Discount bonds are issued below the face value, leading the YTM higher the coupon rate. Because more of the return depend on price appreciation at maturity, green bonds tend to be longer-dated and more sensitive to interest-rate fluctuations; hence, they are more popular with investors who value capital gains over steady income. Firms with low credit rating or when facing weak demand tend to issue at discount. The lower issue price automatically lifts the YTM until it matches the risk premium that investors require. Besides, the smaller coupon also helps ease immediate cash outflow obligations, this is advantageous for issuers facing tight liquidity. In short, a discount bond allows a firm to raise funds under tougher market conditions by exchanging immediate coupon savings for a higher promised return at maturity.

As discussed in Section 2.1, prior research on green bond pricing in the US corporate market yield inconclusive results. The matching-based studies often report little to no pricing advantage and it contrasts with evidence from other markets. Given these mixed findings and the structural characteristics of the US corporate bond market, this study examines whether a green discount exists. This motivates:

*Main Hypothesis 1: Green discount exists in the US corporate bond market.*

Building on *Main Hypothesis 1*, the following sub-hypotheses examine potential drivers of the pricing differential.

The first mechanism is market demand. In the microeconomic theory, market prices are determined by the interaction of the quantity of supply and the quantity of demand. If supply remains constant while demand increases, the upward pressure on demand will lead to a rise in price. In the green bond market, the market demand plays a crucial role

in shaping the bond pricing like so. As noted by Lin et al. (2023), investor sentiment amplified by greenwashing can distort this balance and further inflate bond yield due to their excessive demand driven by perceived environmental value.

Liquidity measures how cheaply and quickly a security trades and it is commonly used in the literature as a proxy for demand. The green bond market has historically faced thin trading volumes and supply-demand imbalances, making liquidity a key explanatory factor (Febi et al., 2018). Following Löffler et al. (2021), this study uses the bond's bid-ask spread to measure liquidity. This approach was also used by Kapraun et al. (2021) and Fatica et al. (2021) where liquidity metrics was used to capture demand-side dynamics in the pricing of sustainable bonds. Higher liquidity, shown as the narrower bid-ask-spread, indicates greater investor interest.

In the context of green bonds, strong demand may reflect a growing investor preference for sustainable assets, which can lead to more favorable pricing for issuers. If investors are willing to accept lower returns for environmental alignment, this should translate into a smaller green discount:

*Sub-hypothesis 1.1: higher market demand reduces  $GD_{i,t}$ .*

The second mechanism is a negative consequence of information asymmetry known as greenwashing which introduces reputational and pricing risks. The information asymmetry issue arises when one party involved in a transaction possesses more or better information than the other. Noted by Lin et al. (2023), this informational gap allows firms to potentially mislead investors through symbolic disclosures or greenwashing, especially when verifiable ESG metrics are lacking. As explained in section 1.2, the requirements for ESG-related disclosures are vague, this amplifies the information gap, making information asymmetry a serious risk in the US green bond market. Noted by Bachelet et al. (2019), this risk is particularly pronounced when green bonds lack third-party verification, which reduces credibility and may result in higher required yields from

investors. In the US, the relatively inexpensive environment to procure a SPO, paired with the lack of SEC oversight of issuing a green bond, makes it cheap and easy. Tatomir et al. (2023) similarly contend that due to the low cost of greenwashing, combined with poor regulatory enforcement, firms are more inclined engage in symbolic and superficial ESG claims. This damages market trust and can distort capital allocation in sustainable finance.

When investors suspect an issuer exaggerate their environmental commitments, the confidence in the green label weakens. This loss of trust can translate into a risk premium, pushing yields upward and potentially offsetting any pricing benefit. Greenwashing thus represents a counterforce that can widen the GD:

*Sub-hypothesis 1.2: higher Greenwashing is associated with a larger  $GD_{i,t}$ .*

## **4.2 Main Hypothesis 2: Greenwashing Determinants**

Although *Sub-hypothesis 1.2* focuses on the bond-level consequences of greenwashing, it does not address its underlying drivers. Greenwashing typically originates from firm-level strategic behavior which signals how management manages and communicates its ESG positioning. Flammer (2021) explains, the issuance of green bonds functions as a credible signal of a firm's commitment to environmental sustainability and it helps differentiate environmentally responsible firms from others. Zhang et al. (2022) similarly underlines that signaling through green behaviors, including disclosures and certifications, is a strategic response by firms to shape market perceptions. These signals can influence investment flows, particularly from ESG-oriented or long-term investors, even when direct environmental performance outcomes are less immediately visible.

However, when a firm misrepresents or exaggerates the environmental benefits of their activities, the positive signaling could turn to a greenwashing risk. Such behavior is likely

shaped by the issuer's ESG profile and financial fundamentals. Some firms-level attributes combined ESG performance patterns may lead to a greater divergence between their stated ESG claims and actual environmental impact, thus influencing the intensity of greenwashing. It is crucial to identify these firm-level determinants for understanding why greenwashing occurs and how it may ultimately affect market pricing. This leads to:

*Main Hypothesis 2: Greenwashing behavior is associated with firm-specific characteristics.*

First, a firm's credit quality is a key indicator of its overall risk profile. Firms with weaker credit quality may experience greater pressure to attract favorable financing or improve market perception. In such cases, it could be incentivized to use green signaling as a strategic tool in order to enhance its market appeal without necessarily improving its underlying ESG performance. This dynamic suggests that financially constrained firms may be more inclined to rely on symbolic disclosure to attract sustainability-focused capital:

*Sub-hypothesis 2.1: Firms with lower credit quality (i.e., higher credit risk) are more likely to engage in greenwashing.*

Beyond the credit risk, a firm's ESG performance profile may also influence its propensity to greenwash. Aggregate ESG scores can obscure offsetting effects across their underlying dimensions, examining each pillar separately becomes more appropriate, because it allows for the identification of specific areas where underperformance could create incentives for symbolic disclosure, particularly if firms seek to mask weaknesses in one domain by emphasizing strengths in another. Since green bonds primarily intend to fund environmental initiatives, the environmental (E) pillar should play a significant role. Stronger environmental performance supports credible sustainability efforts, reducing the perceived need to mislead investors through exaggerated claims. As a result, firms with robust environmental practices are less likely to engage in fraudulent sustainability marketing as a way to improve their market image:

*Sub-hypothesis 2.2: Firms with stronger environmental performance are less likely to greenwash.*

In contrast, although the social (S) pillar may still influence perceptions of corporate responsibility for the same reason, its relevance to green bond issuance is less direct:

*Sub-hypothesis 2.3: Firms with stronger social performance are less likely to greenwash, but to a lesser extent than their environmental score.*

Greenwashing also appears to be the result of deliberate strategic positioning at the firm level. Firms with stronger governance practices may be particularly capable of engaging in symbolic or misleading ESG disclosures, because their procedural rigor and narrative framing provide tools to signal compliance with their sustainability goals without necessarily achieving significant environmental improvements. According to Marquis and Michael (2012), greenwashing represents a symbolic strategy: firms strategically employ selective disclosure to maintain legitimacy, especially when they are vulnerable to stakeholder criticism. From their point of view, stronger governance does not prevent greenwashing, rather, it may facilitate more sophisticated forms of symbolic signaling in an environment where the system emphasizes formal compliance to reporting frameworks over the achievement of practical outcomes.

This perspective is also consistent with the empirical findings of Burbano and Delmas (2011): firms with strong a governance structure may be better able to greenwash. Institutional capacity for disclosure can help with a firm's ability to construct appearance of ESG alignment. Although corporate governance is typically associated with greater transparency and accountability, it may paradoxically increase a firm's potential greenwash by providing infrastructure for symbolic compliance.

*Sub-hypothesis 2.4: Firms with stronger governance scores are more likely to greenwash.*

Finally, the investor sentiment can influence on corporate sustainability signaling. Following Flammer (2021) and Lin et al. (2023), Tobin's Q is used as an indirect proxy for investor sentiment. Tobin's Q is the ratio of a firm's market value to its total assets<sup>2</sup>. Although the wedge between market value and book assets reflects the general residual value beyond recorded tangibles, intangibles such as growth expectations, brand, technology, organizational capital, and ESG reputation, retain capitalized and serve as standard proxy for investor sentiment in research. A higher Tobin's Q ratio indicates more optimistic investor expectations. As optimism is generally beneficial, firms enjoying greater investor trust may face less pressure to artificially inflate their ESG profile. In such cases, the management has fewer incentives to rely on symbolic disclosures, because no external force could alter its the existing operating integrity and its genuine sustainability practices:

*Sub-hypothesis 2.5: Firms with investor sentiment, e.g., higher Tobin's Q, are less likely to greenwash.*

Note that market demand and investor sentiment are different concepts. Market demand reflects the market-based appetite and is typically captured through trading activity and liquidity measures, such as the bid-ask spread. In this study, it enters the bond-level regressions that estimate greenium or green discount. In contrast, investor sentiment represents the collective expectations that investors hold about a firm's valuation and prospects. Unlike demand, sentiment is intangible and is often inferred through proxies like Tobin's Q ratio. In this study, it enters the firm-level regressions that explains the

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<sup>2</sup>  $\frac{\text{market value of equity} + \text{book value of debt}}{\text{book value of debt}}$

greenwashing risk. it is important to distinguish these two variables to better understand the models.

## **5. Data**

### **5.1 Databases and Explanations**

#### **5.1.1 Bloomberg**

The Bloomberg Green Bond database is a widely recognized and authoritative source for identifying and tracking green bonds across global markets. It classifies green bonds using the “Bloomberg MSCI Green Bond Index” methodology, which applies strict eligibility criteria to ensure that included bonds commit 100% of their proceeds to clearly defined environmental projects. These may include projects in renewable energy, energy efficiency, pollution prevention, and climate change adaptation. The database uses the “Green Instrument Indicator” to flag securities that meet these criteria. It is an important tool for researchers, investors, and analysts seeking reliable and standardized data on labeled green bonds.

The sample of US corporate green bonds is constructed using Bloomberg’s “Fixed Income Search” function. The search parameters were restricted to instruments classified as “Corporate” and to issuers with a “Country/Region of Incorporation” designated as the “United States of America”. To identify green bonds, the “Green Instrument Indicator” is set to “Yes”; according to Bloomberg, this flags that the bonds whose issuers “states that the net proceeds of the instrument include environmental projects or activities” (Bloomberg, 2025). The issuance year is further restricted to 2013 or later, as the first green bond was officially issued in the US in 2013. The final dataset comprises 409 eligible green bonds issued by 146 unique corporate issuers over the period 2013 through February 2025, totaling amount of approximately USD\$190 billions. From this dataset, a

set of bond-level variables is extracted for empirical analysis, including: Issuer Name, CUSIP, Issuer Industry, S&P Credit Rating, Coupon Rate (Cpn), Coupon Type, Yield to Maturity (Mid), Maturity Date, Par Amount, Pricing Date, Bid-Ask Spread (LQA), Years to Maturity (from today), Modified Duration (Mid), and Amount Issued. This bond-level dataset provides essential information for evaluating pricing, liquidity, risk characteristics, and structural features of the green bonds in the sample. A sample of green bonds is provided in Appendix Table A1.

To facilitate quantitative analysis, the S&P credit ratings of each bond are converted into a numerical scale. The highest rating, AAA, is assigned a score of 1, followed by AA+ as 2, and so forth in descending order of credit quality. Bonds with the lowest rating of B-, as well as those with unrated, are assigned the maximum score of 16. This transformation enables the incorporation of credit quality as a continuous variable in regression models. A full table mapping S&P credit ratings to numerical values is provided in Appendix Table A2. To construct a firm-level measure of credit quality, the credit ratings of all bonds issued by each firm are grouped and computed the average numerical credit rating. This average proxies for the firm's overall credit standing.

The firm-level dataset, including financial and ESG data, is obtained from Bloomberg using the "Spreadsheet Builder" function within Microsoft Excel, which enables direct extraction of historical data from the Bloomberg terminal. The "Time Series Table" option is selected to compile historical data for a group of securities, with each firm identified by its equity ticker symbol. These tickers are entered in the Security field, and the desired variables specified in the "Select Fields" section. The "Period Calendar" is set from fiscal year 2013 to the most recent available year (2025), with "Periodicity" defined as "Fiscal Annual". Out of the 146 unique issuers in the green bond sample, 7 are privately held and lacked publicly available data - that represents 26 bonds, leaving 139 publicly listed firms for firm-level analysis. For each firm, annual observations are collected for the following variables: WACC Cost of Debt (After Tax), Total\_Assets, Financial Leverage, Return on

Assets, Current Ratio, ESG Disclosure Score, and Tobin's Q Ratio. The extracted datasets are formatted as firm-year panels in Excel to help facilitate reshaping and merging with the bond-level dataset in subsequent stages of the analysis.

Next, to calculate  $GD_{i,t}$  (defined in Section 3.1), the bond-level cost of debt data are first transformed from wide to long format by unpivoting each table so that each row represented a unique firm-year pair with its associated variables. This firm-year key was then used to merge with the bond-level dataset by matching issuer names and issuance years. Each green bond is thus assigned the corresponding annual after-tax cost of debt for its issuing firm. The green discount is then computed as the difference between the observed YTM in the bond-level dataset and stored as a separate variable alongside other bond characteristics for further analysis.

Other firm-level variables, including firm fundamentals, Tobin's Q, and ESG disclosure scores, are organized using the same unpivoting procedure. After merging these variables with the bond-level dataset via the firm-year key, the data are aggregated by issuer and year, with group-level means calculated for each variable. Observations with missing values for any key variable were excluded from the final sample to ensure consistency across specifications.

#### 5.1.2 Asset4

The other component of the *GWScore* as well as the separate E, S, and G pillar scores are obtained from the Refinitiv/Asset4 database using the firm ISIN as identifiers. The Refinitiv/Asset4 ESG database provides standardized and comparable ESG metrics for publicly listed companies worldwide. It covers over 9,000 firms in more than 80 countries, offering 500+ ESG data points and 250+ key performance indicators. The data is sourced from publicly available sources, and it undergoes a strict quality assurance process, it

enables researchers and investors to assess corporate ESG performance consistently across time and geography.

Specifically, the following data are obtained for the tests<sup>3</sup>:

- ESG score: an overall company score based on the self-reported information in the environmental, social and corporate governance pillars;
- ESG Combined Score: an overall company score based on the reported information in the environmental, social and corporate governance pillars (ESG Score) with an ESG Controversies overlay;
- Environment Pillar Score: the weighted average relative rating of a company based on the reported environmental information and the resulting three environmental category scores;
- Social Pillar Score: the weighted average relative rating of a company based on the reported social information and the resulting four social category scores; and
- Governance Pillar Score: the weighted average relative rating of a company based on the reported governance information and the resulting three governance category scores.

Following the same treatment applied to the Bloomberg bond data, these scores are first merged with the bond-level dataset based on issuer name and issuance year. The merged data are then grouped by issuer and year, and the relevant variables are aggregated using group-level means to generate a consolidated firm-year panel suitable for regression analysis, excluding observations with missing values on any key variables.

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<sup>3</sup> These definitions are provided in the Refinitiv Asset4 ESG Glossary Refinitiv. (2024). *Asset4 ESG Glossary* ([Internal Excel dataset/document]). Available from Refinitiv Asset4 database (subscription required) , they were accessed through the proprietary Refinitiv database.

To compute the *GWScore* at the bond level, both the ESG disclosure and ESG performance scores are first normalized by computing the sample mean and standard deviation for each firm-year observation across the dataset; *GWScore* is then derived as the difference between the two normalized values. This bond-level *GWScore* is subsequently aggregated at the firm level using the same methodology described above, hence ensuring consistency across the dataset for empirical analysis. It is also important to note that the ESG data is only available through 2023 in this database.

To enhance model robustness and minimize multicollinearity between the *GWScore* and related ESG variables, two versions of the greenwashing measure are constructed using ESG performance scores: with and without the ESG controversy component. In the Asset4 database, the ESG performance score is available in two formats: a combined score that incorporates the ESG controversy score, and a pillar-based score that is the sum of the three ESG pillar scores without including controversies. The latter separates between reported performance and negative event data. Consistent with the two measurements, the *GWScore<sub>combo</sub>* is denoted to represent *GWScore* calculated based on ESG combined performance score and *GWScore<sub>sep</sub>* to represent the pillar-based ESG performance score. In the subsequent empirical analysis, *GWScore<sub>combo</sub>* and *GWScore<sub>sep</sub>* are applied to different levels of analysis, they are then also interchanged across specifications to assess the stability of results. A sample of calculated *GWScore* values is provided in Appendix Table A3.

## 5.2 Presentations of Data

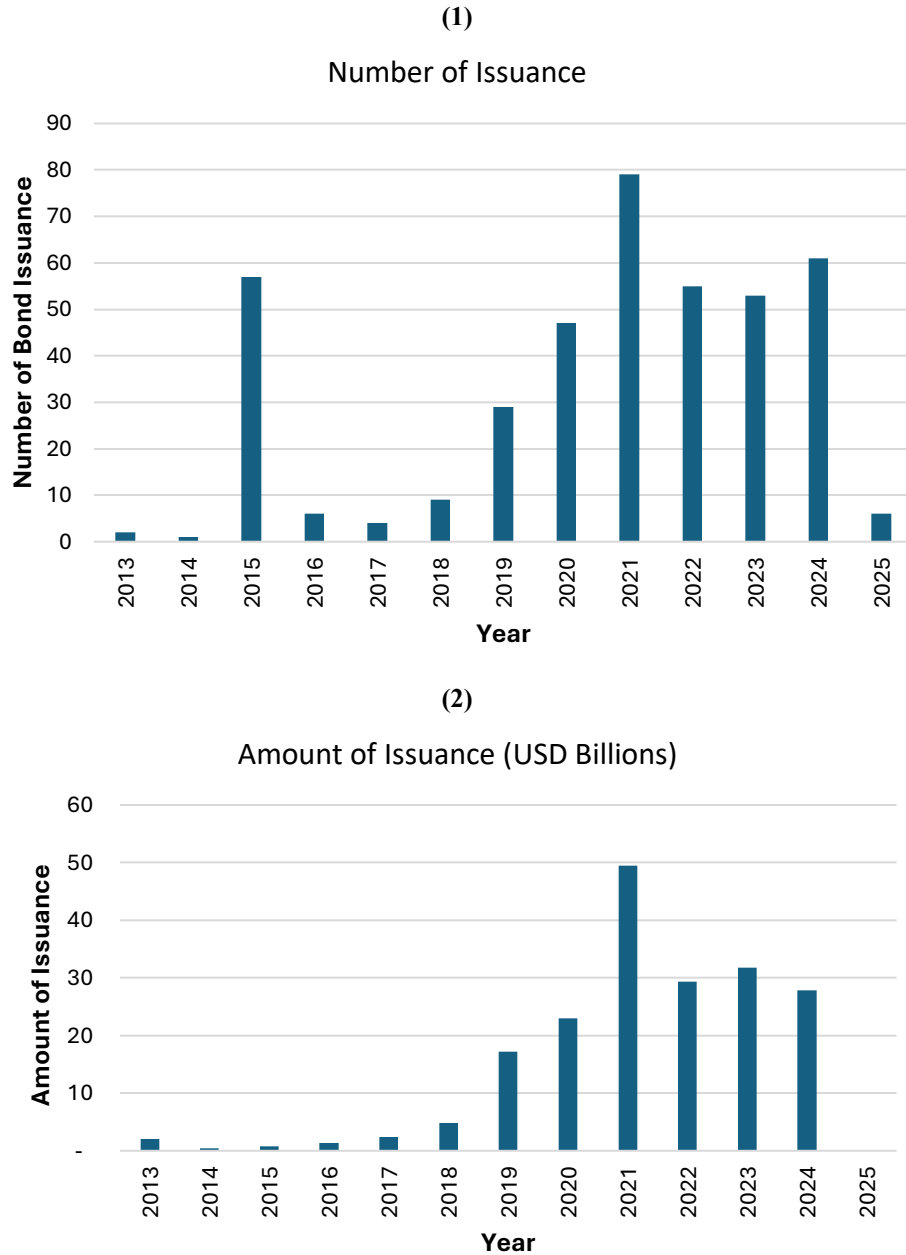
### 5.2.1 Description of Statistics at the Bond-Level

Based on the final bond-level dataset of 409 green bonds issued by 146 issuers, the evolution of the green bonds in the US corporation market since 2013 shows a clear growth trajectory, shown in the Figure 2. Issuance activity commenced modestly, with a small and first peak in 2015, although the total issuance amount remained minimal in that

year. A more sustained expansion began in 2017 and accelerated to a peak in 2021 with over 75 new bond issuances aggregating approximately USD 50 billion. While there was a slight decline in both issuance count and total volume in subsequent years, the market base remained strong and stable, with annual issuance consistently exceeding 60 bonds and total dollar amount averaging USD 30 billion. Note that the apparent drop in 2025 figures is attributable to incomplete data for the year, rather than a structural contraction in the market activity.

In terms of the industry distribution, the green bond market exhibits a heavy concentration. The financial, industrial, and utility-electric sectors together account for approximately 89% of total issuances (Figure 3, Graph (1)). Collectively, these sectors represent a cumulative issuance volume of USD 55.29 billion over the sample period (Figure 3, Graph (2)). Such concentration on capital-intensive industries presents their importance in driving corporate green financing in the US market as well as the reliance of the market growth on a limited set of sectors.

**Figure 2: Number and Amount of Green Bonds Issued by Year**

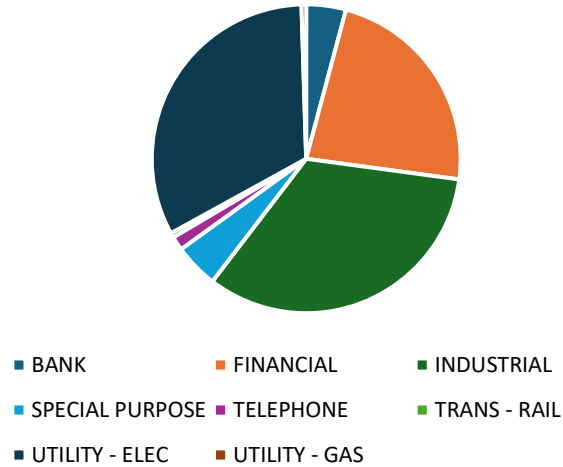


*Figure 2.* This figure shows the number and amount of green bonds issued annually by U.S. corporate entities. Graph (1) shows the number of issuance and Graph (2) shows the amount, measured in U.S. dollars.

**Figure 3: Number and Amount of Issuance by Industry**

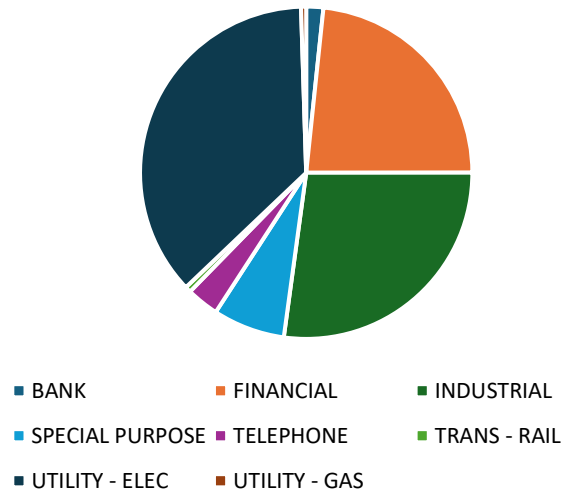
(1)

Number of Issuance



(2)

Amount of Issuance in Billions



*Figure 3.* This figure shows the number and amount of annual green bond issuance in the US corporate market. Graph (1) presents the distribution of green bond issuances across industry sectors in the US corporate market. Graph (2) shows the cumulative US corporate green bond issuance volume by industry, measured in U.S. dollars.

A summary of description of key statistics is presented in Table 2. The average coupon rate among green bonds in the sample is 4.17%, with an average maturity of 8.66 years and a modified duration of 5.43 years - indicating a moderately long-term risk profile. The average S&P credit rating, expressed numerically, is approximately 5, corresponding to an A+ rating. Notably, the average YTM of 7.73% exceeds the average coupon rate, this suggests that many bonds in the sample are trading at a discount, consistent with the expectation of the presence of green discounts in this segment of the market.

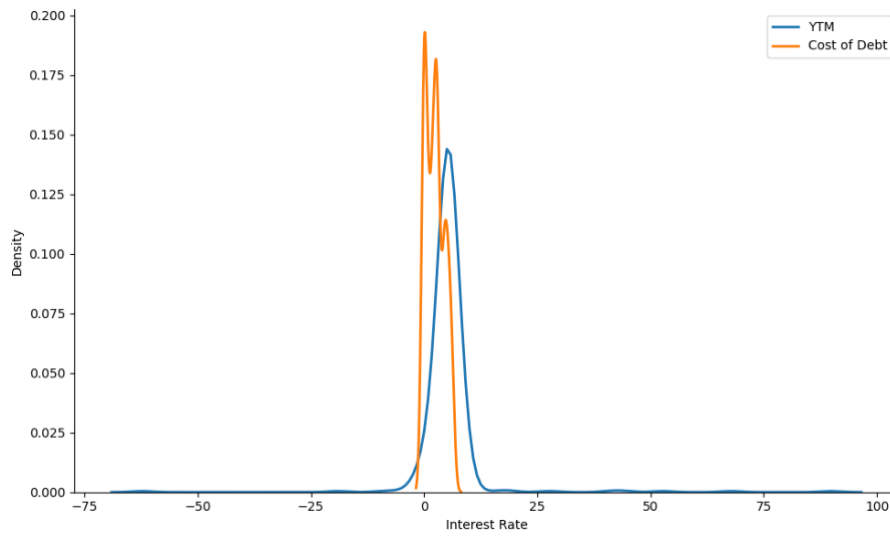
**Table 2: Summary of Key Statistics at Bond-Level**

| <b>Variable</b>           | <b>Mean</b> | <b>Std.</b> | <b>Min</b> | <b>Max</b>   |
|---------------------------|-------------|-------------|------------|--------------|
| Bid-Ask Spread            | 0.59        | 0.40        | 0.03       | 1.90         |
| Coupon                    | 4.17        | 2.29        | -          | 18.50        |
| Maturity (in years)       | 8.66        | 8.93        | -          | 36.28        |
| Face Value                | 14,013.04   | 89,006.85   | 169.33     | 1,122,140.00 |
| Modified duration         | 5.43        | 4.69        | -          | 16.67        |
| S& P Credit Rating (in #) | 5.01        | 4.11        | -          | 15.00        |
| YTM                       | 7.73        | 44.91       | -109.16    | 890.69       |

*Table 2.* This table summarises the statistics for key bond-level variables of the 409 US corporate green bonds in the sample. Bid-Ask Spread is the price differential between a buyer and a seller, it proxies for bond liquidity, narrow spreads indicate higher liquidity. Coupon is the annual interest paid to bondholders expressed as a percent of face. Maturity is the time until repayment. Face (par) value is the nominal amount to be repaid at maturity. Modified duration is percentage change in the bond price when there is a 1% change in interest rate. S&P Credit Rating reflects the creditworthiness of a bond issuer assessed by Standard & Poor's, with higher ratings indicating higher default risk and weaker financial stability. YTM is the total return anticipated by investors if the bond is held to maturity, it is usually compared with the coupon rate to determine if a bond trades at a discount or premium.

To further illustrate the potential existence of a green discount, kernel density estimates are performed to visualize the distributions of YTM and  $R_d^{WACC}$ . As shown in Figure 4, the YTM distribution reveals a clear rightward shift relative to  $R_d^{WACC}$ , this means that, on average, green bonds in the sample are issued at yields exceeding the firms' estimated financing costs. This divergence visually supports the hypothesis that a green discount may exist in the US corporate green bond market.

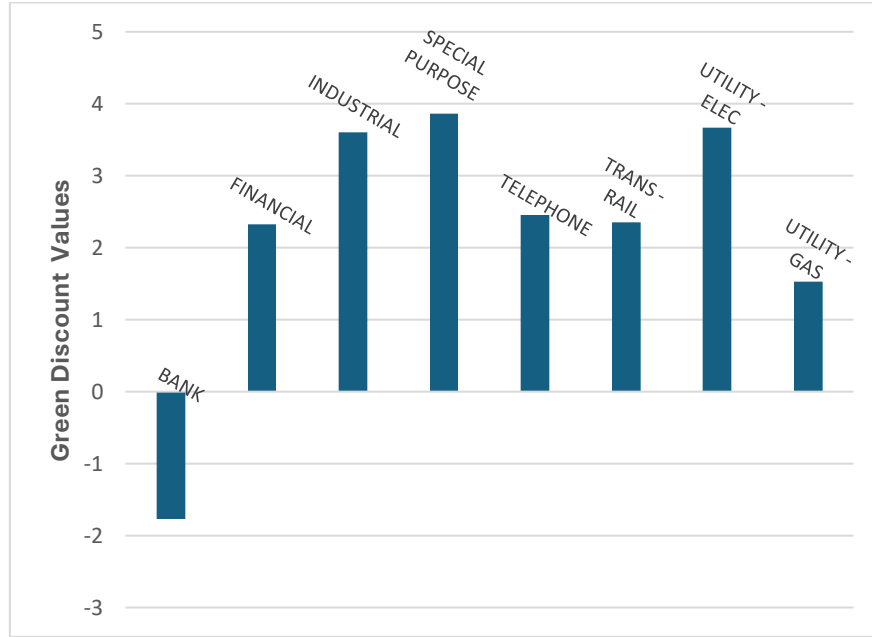
**Figure 4: Kernel Density Estimates of YTM and Cost of Debt**



*Figure 4.* This figure compares the distributions of green bond yields (YTM) with the firms' estimated cost of debt. The horizontal axis represents the interest rate in percentage terms; the vertical axis indicates the density. The visual spread highlights the divergence between market pricing and internal financing benchmarks.

Figure 5 presents the average green discount by industry; a positive value indicates green discount. The figure shows that most industries exhibit a green discount, with the Special Purpose, Utility-Electric, and Industrial sectors experiencing the highest average values, all around 3.5 to 4 percentage, this denotes that firms in these sectors may be penalized more heavily by the market when issuing green bonds. In contrast, the Banking sector is the only one showing a negative average value, signaling that green bonds issued by banks may enjoy slightly more favorable pricing. The Financial, Telephone, and Transportation-Rail sectors show moderate discounts, whereas the Utility-Gas sector exhibits a smaller pricing gap. These patterns highlight the industry-specific nature of green bond pricing, indicating that investor perceptions and risk assessments vary significantly across sectors in the US corporate green bond market.

**Figure 5: Average Green Discount by Industry**



*Figure 5.* The figure shows the average green discount across industry in the U.S. corporate green bond market. Values above zero indicate the presence of a green discount (i.e., higher yields relative to estimated cost of debt); negative values reflect a green premium. Industry codes follow Bloomberg classifications.

### 5.2.2 Summary of Statistics at the Firm-Level

The firm-level dataset is constructed by aggregating bond-level observations by issuer and year, taking the mean of key variables for each firm-year pair. Table 3 provides a summary of description of key statistics at the firm-level. The  $GWScore^4$  has a mean of 0.11 (std = 0.75) and ranges from -2.17 to 0.56, indicating substantial variation in the divergence between ESG disclosure and actual performance. The average credit rating is 5, suggesting that most firms in the sample fall into the mid- to lower-investment-grade category. The mean ESG combo score is 5 while the mean ESG pillar scores are 51.36 for environmental, 56.33 for social, and 52.88 for governance, reflecting relatively high ESG performance across firms, although with notable dispersion. The Tobin's Q ratio averages 3.40, with a wide range extending up to 219.41, suggesting significant variation

<sup>4</sup> For descriptive purposes,  $GWScore_{combo}$  is used in this sub-section, for it is expected to yield comparable results to those of  $GWScore_{sep}$ .

in market valuation expectations across firms. Firm fundamentals reveal an average log of total assets of 10.67, consistent with a sample dominated by mid- to large-sized firms. Leverage averages 4.91, and the mean return on assets (ROA) is 0.89% with a wide range that includes some highly negative value.

**Table 3: Summary of Key Statistics at Firm-Level**

| <b>Variable</b>   | <b>Count</b> | <b>Mean</b> | <b>Std</b> | <b>Min</b> | <b>Max</b> |
|-------------------|--------------|-------------|------------|------------|------------|
| GWScore           | 196          | 0.11        | 0.75       | -2.17      | 0.56       |
| CreditRating      | 409          | 5.01        | 4.10       | 0.00       | 15.00      |
| ESG_combo Score   | 199          | 47.87       | 23.50      | 8.84       | 93.13      |
| EScore            | 199          | 51.36       | 29.29      | 1.35       | 96.80      |
| SScore            | 199          | 56.33       | 23.53      | 2.69       | 96.71      |
| GScore            | 199          | 52.88       | 29.02      | 6.86       | 97.85      |
| InvestorSentiment | 322          | 3.40        | 12.46      | 0.84       | 219.41     |
| LogFirmSize       | 409          | 10.67       | 1.95       | 3.32       | 17.80      |
| Leverage          | 409          | 4.91        | 3.08       | 1.21       | 25.60      |
| ROA               | 409          | 0.89        | 7.48       | -76.95     | 15.69      |

*Table 3.* This table summaries statistics for the firm-level dataset constructed by aggregating bond-level data by issuer and year. *GWScore* is the greenwashing score, calculated by Equation (2) from section 3.2. *ESG\_combo Score*, *EScore*, *SScore*, and *GScore* are ESG Combined Score, Environment Pillar Score, Social Pillar Score, and Governance Pillar Score, respectively, as per definition (section 5.1.2) from the Asset4 database. *InvestorSentiment* is investor sentiment, proxied by Tobin’s Q score, obtained from the Bloomberg database. *LogFirmSize* is measured by the logarithm of total assets, it indicates the scale of a company’s market share, larger firms are perceived as more stable and less risky. *Leverage* is measured by the current ratio (current assets divided by current liabilities), it reflects the firm’s ability to meet near-term obligations; lower values may signal financial strain. *ROA* (return on assets, total income divided by total assets), it measures the firm’s profitability and captures how efficiently it utilizes its resources to generate earnings.

Figure 6 presents a comparison of average ESG disclosure and performance disclosure scores by industry. Across most sectors, the performance scores tend to exceed disclosure scores, which suggests a tendency toward underreporting, rather than exaggeration, by industry. Notably, the Special Purpose and the Financial categories show the largest discrepancies this reveals a potential “green” sign with little indication of greenwashing. Industries such as Telephone and Utility-Elec exhibit relatively close scores. In contrast,

the Industrial sector shows a slight overreporting. Overall, the variation exists but do not seem to suggest a presence of greenwashing by industry.

**Figure 6: Comparison of ESG Disclosure and Performance Scores**

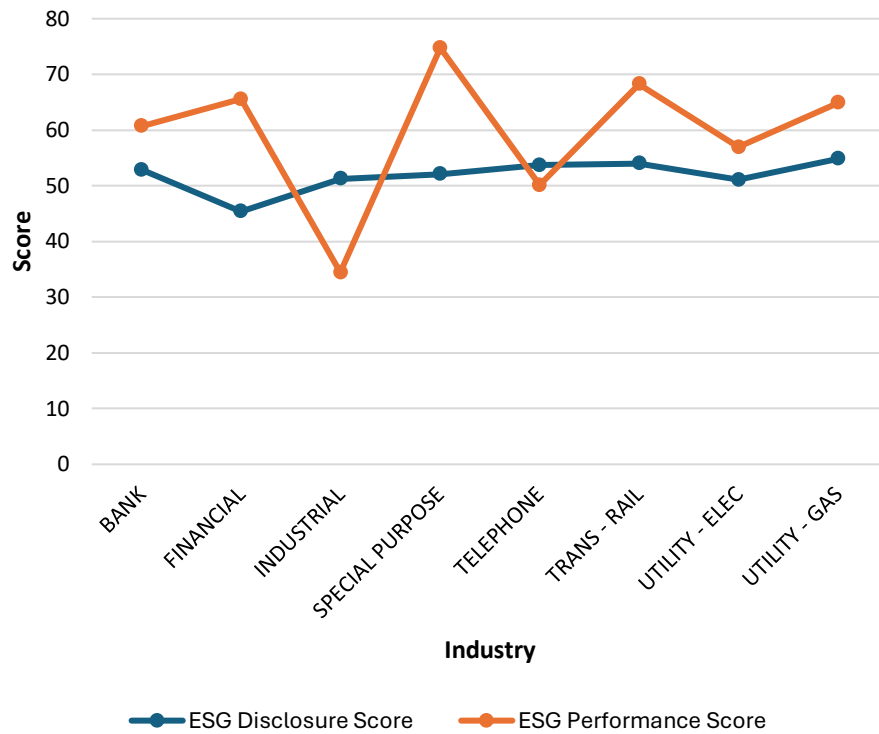


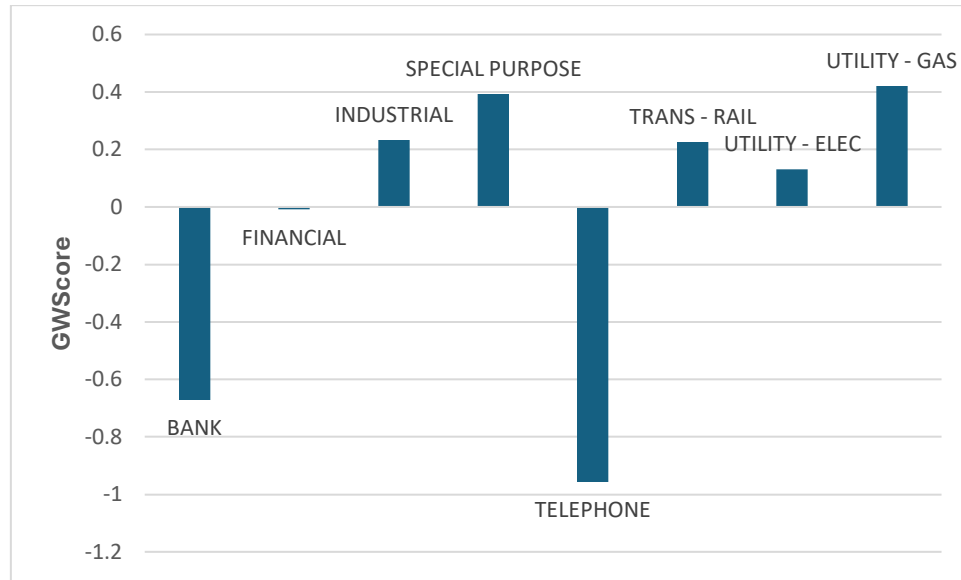
Figure 6. This figure compares industry-level averages of ESG disclosure and performance scores. Values above the 45-degree line indicate underreporting (performance exceeds disclosure); values below suggest potential overreporting.

Figure 7 illustrates the average  $GWScore^5$  by industry, higher values are interpreted as a higher likelihood of greenwashing. The Financial and Special Purpose sectors exhibit negative average values, consistent with the previous comparison of the disclosure and performance scores and implies relatively low degree of greenwashing. Conversely, the Industrial sector displays the highest average value exceeding 1, implying the possible greenwashing existence - this aligns with the overreporting observed in the comparison Figure 7. The Telephone and Utility-Electric sectors show moderate values which is also

<sup>5</sup>  $GWScore_{sep}$  is used here.

in line with the earlier comparison showing minimal discrepancies. In sum, these patterns emphasize that greenwashing is heterogeneous across industries, it also advises that ESG signaling is not uniform across sectors.

**Figure 7: Greenwashing Score by Industry**



*Figure 7.* This figure shows the *GWScore* calculated by Equation (2) across industries. Positive values indicate underreporting (actual performance exceeds disclosure) negative values signal overreporting.

## 6. Models Framework & Estimation Approach

### 6.0 Estimation Roadmap

This section outlines the empirical framework for testing the study's hypotheses.

The analysis proceeds along two complementary dimensions: the bond-level regression examines how security-specific characteristics influence the GD, while the firm-level regression explores ESG scores and the financial ratios determinants of greenwashing behavior. Recall from Section 3:

- $GD_{i,t} = YTM_{i,t} - R_{d,i,t}^{WACC} \quad (1)$
- $GWScore_{i,t} = \frac{ESG\ disc_{i,t} - \overline{ESG\ disc}_{i,t}}{\sigma_{ESG\ disc,i,t}} - \frac{ESG\ perf_{i,t} - \overline{ESG\ perf}_{i,t}}{\sigma_{ESG\ perf,i,t}} \quad (2)$

The choice of  $GWScore_{i,t}$  is based on the distinct analytical objectives of the two regression frameworks. At the bond level, the analysis focuses on pricing dynamics,  $GWScore_{combo}$ , including the ESG controversy scores, captures additional market-relevant credibility signals that may directly influence bond yields. At the firm level, the aim is to examine organizational drivers of greenwashing behavior; here,  $GWScore_{sep}$ , excluding controversies, helps reduce mechanical correlation with other ESG variables and to isolate the divergence between disclosure and performance. The two measures are also interchanged in robustness checks to ensure that the findings are not sensitive to the inclusion or exclusion of controversies in the greenwashing metric.

All continuous variables are standardized or mean-centered where appropriate to improve interpretability and reduce multicollinearity.

Finally, robustness checks using alternative greenwashing measures, clustered standard errors, and reverse-causality tests, and are presented following the quantitative findings and interpretations.

## 6.1 Bond-Level Specification: Green Discount Determinants

### 6.1.1 Regression Model

The analysis begins by testing *Main Hypothesis 1* to examine if the green discount exists in the US corporate market, specifically, a one-way t-test is conducted on the  $GD_{i,t}$  variable to test whether it is statistically different from zero:

$$GD_{i,t} = \theta_0 + \varepsilon_{i,t} \quad (3)$$

Where:

- $\theta_0$  represents the average GD in the sample.

The rejection of the null hypothesis implies the presence of green discount or greenium.

The next step is to explore whether this green discount can be systematically linked to observable bond-level factors. To achieve so, a multivariate Ordinary Least Squares (OLS) regression with industry and year fixed effects was utilised. The dependent variable is  $GD_{i,t}$  is regressed against the regressors like BidAskSpread and GWScore (testing Sub-hypotheses 1.1 and 1.2, respectively), plus the bond-level controls and these continuous controls are mean-centered; all observations with missing fields are removed listwise. Coefficients are interpreted as partial effects conditional on the fixed effects and controls; standard errors are conventional OLS (no clustering in this baseline). For each explanatory variable, a two-tailed t-test is conducted on the estimated coefficient  $\beta_j$ , after controlling for other covariates and fixed effects.  $GD$  is a function of market demand, greenwashing intensity, and other bond-specific controls:

$$GD_{i,t} = \alpha_0 + \alpha_1 MD_{i,t} + \alpha_2 GWScore_{i,t} + X'_{i,t} \alpha + \gamma_{Industry} + \gamma_{Year} + \varepsilon_{i,t} \quad (4)$$

Where:

- $GD_{i,t}$  is the dependent variable, measured as the difference between a bond's observed yield to maturity and its estimated cost of debt;
- $MD_{i,t}$  represents market demand, proxied by the bond's bid-ask spread;
- $GWScore_{i,t}$  is calculated using the  $GWScore_{combo}$ ;
- $X'_{i,t}$  denotes a vector of control variables, including *coupon rate, maturity, log of face value, modified duration, and credit rating*;

- Industry ( $\gamma_{Industry}$ ) and year ( $\gamma_{Year}$ ) fixed effects control for unobserved heterogeneity across sectors and time periods.

The rejection of the null, either positive or negative, indicates a statistically significant association.

For both regressions, the analysis will draw on the bond-level dataset of 409 observations.

### 6.1.2 Expected Signs

- $GD$  exists in the US corporate green bond market:  $\theta_0 \neq 0$
- Wider bid-ask spreads (lower liquidity) are to increase  $GD$ :  $\alpha_1 > 0$
- Higher  $GWScore$  to increase  $GD$ :  $\alpha_2 > 0$

## 6.2 Firm-Level Specification: Greenwashing Determinants

### 6.2.1 Regression Model

To investigate the firm-level determinants of greenwashing behavior, an OLS regression with two-way fixed effects for industry and year is used to test *Main Hypothesis 2*, using a panel dataset of 196 non-null observations structured by issuer and year. Similarly, a two-tailed t-test with two-way industry and year dummies is used to check if each parameter is significantly different from zero in either direction, with the firm-level  $GWScore$  ( $GWScore_{sep}$ ) being the dependent variable.  $GWScore$  is a function of credit quality, ESG pillar performance scores, investor sentiment, and firm financial fundamentals:

$$GWScore_{i,t} = \beta_0 + \beta_1 CR_{i,t} + \beta_2 E_{i,t} + \beta_3 S_{i,t} + \beta_4 G_{i,t} + \beta_5 IS_{i,t} + Z'_{i,t} \beta + \gamma_{Industry} + \gamma_{Year} + \varepsilon_{i,t} \quad (5)$$

Where:

- $GWScore_{i,t}$  is the dependent variable, measured as the difference between a firm's normalized ESG disclosure and normalized performance scores;
- $CR_{i,t}$  is the S&P rating expressed in numerical form with higher values indicating lower credit quality (i.e., higher credit risk);
- $E_{i,t}$ ,  $S_{i,t}$  and  $G_{i,t}$  represent the firm's environmental, social, and governance pillar scores, respectively;
- $IS_{i,t}$  denotes investor sentiment, proxied by Tobin's Q;
- $Z'_{i,t}$  denotes a vector of control variables, including the *log of total assets*, *leverage*, and *ROA*;
- Industry ( $\gamma_{Industry}$ ) and year ( $\gamma_{Year}$ ) fixed effects are to absorb time-invariant sectoral influences and macroeconomic shocks.

### 6.2.2 Expected Signs

- Lower credit quality (higher credit rating) to increase  $GWScore$ :  $\beta_1 > 0$ ;
- Stronger environmental and social pillar scores to reduce  $GWScore$ :  $\beta_2, \beta_3 < 0$ ;
- Lower governance pillar score to increase  $GWScore$ :  $\beta_4 > 0$ ;
- Higher Tobin's Q to decrease  $GWScore$ :  $\beta_5 < 0$ .

## 7. Results & Interpretations

### 7.1 Quantitative Findings for Main Hypothesis 1 and Robustness Checks

#### 7.1.1 Quantitative Findings and Implications

First, the existence of green discount is confirmed in the US corporate market. The full bond-level sample of 409 observations produces a mean GD of 3.08 with a t-statistic of

7.99 ( $p < 0.001$ ). Table 4 shows the result of the test; it confirms that green bonds are indeed priced at a disadvantage relative to firms' estimated financing costs.

**Table 4: Paired-Sample t-Test of Main Hypothesis 1**

| <i><b>Statistic</b></i> | <i><b>Green-Discount</b></i> | <i><b>Benchmark (0)</b></i> |
|-------------------------|------------------------------|-----------------------------|
| Mean                    | 3.08                         | 0                           |
| Variance                | 60.94                        | 0                           |
| Observations            | 409                          | 409                         |
| Degrees of freedom (df) | 408                          |                             |
| t-statistic             | 7.99                         |                             |
| p-value (two-tailed)    | 0.00                         |                             |

*Table 4.* This table reports the results of a paired-sample t-test comparing the mean green discount against a benchmark value of zero. The null hypothesis is that the mean green discount is different from zero. The test rejects the null at the 1% significance level ( $p < 0.01$ ), indicating that the average green discount statistically differs from zero.

Economically, this result suggests that, on average, the issuers of US corporate green bonds face a yield that is approximately 3.08% above their own benchmark cost of debt. From the issuer's perspective, this represents a financing cost disadvantage, as they must pay more to raise capital than they would under conventional borrowing conditions. From the investor's perspective, the same pattern appears as a yield premium, reflecting higher returns for holding these bonds. This cost-return asymmetry is consistent with the presence of a green discount in the US corporate bond market.

The findings also refine existing signaling theory. In the lightly regulated US market, the "green" label alone no longer conveys credible information to investors. When third-party certification or verifiable use-of-proceeds reporting is absent, investors appear to discount the label's signaling value and instead price the bond according to conventional credit and liquidity risk assessments. In some cases, this may even result in a pricing penalty, what this study terms the green discount, as a precautionary hedge against reputational and liquidity risks. This stands in contrast to earlier theoretical predictions that labels could

deliver a persistent premium, highlighting that signaling effectiveness depends critically on institutional and regulatory context.

The finding also provides an important empirical anchor for subsequent analysis. The established existence of a measurable green discount has created the foundation for examining its potential drivers. The statistical results for the two subsequent sub-hypotheses are shown in Column (1) in Table 5 and they will be interpreted individually.

**Table 5: Regression Results for Main Hypothesis 1**

| Variable       | (1) $GWScore_{combo}$ | (2) $GWScore_{sep}$ |
|----------------|-----------------------|---------------------|
| BidAskSpread   | 8.1633**<br>(3.420)   | 5.5068*<br>(3.231)  |
| GWScore        | -2.0292<br>(1.339)    | 1.3605<br>(1.289)   |
| Coupon         | 1.0366*<br>(0.619)    | 1.0181<br>(0.620)   |
| Maturity       | -0.0312<br>(0.450)    | -0.0345<br>(0.461)  |
| LogFV          | -0.4991<br>(1.010)    | -0.2843<br>(1.097)  |
| ModDuration    | -0.4416<br>(0.800)    | -0.4096<br>(0.815)  |
| CreditRating   | -0.8777***<br>(0.325) | -0.7776*<br>(0.313) |
| Industry FE    | Yes                   | Yes                 |
| Year FE        | Yes                   | Yes                 |
| Observations   | 134                   | 134                 |
| R-squared      | 0.263                 | 0.242               |
| Adj. R-squared | 0.117                 | 0.092               |
| F-statistic    | 1.8                   | 1.163               |
| p(F-statistic) | 0.0249                | 0.0556              |

**Note:**

Significance levels are denoted as: \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ . Robust standard errors are reported in parentheses.

Table 5. This table reports OLS regression of Sub-hypotheses 1.1 and 1.2. All regressions include industry and year fixed effects (coefficients not reported).

- *Sub-hypothesis 1.1: higher market demand reduces  $GD_{i,t}$*

Market demand, proxied by the bid-ask spread, is positively and significantly associated with the green discount at the 5% significance level ( $\alpha_1 = 8.16$ ,  $p = 0.019$ ), consistent with the expectation. A one-unit widening of the spread is associated with an estimated 8.16% increase in GD. This relationship is also economically meaningful, for liquidity constraints (i.e., reduced market demand and wider spreads) can translate into higher yields relative to the firm's estimated financing costs, thereby amplifying the pricing disadvantage for green bonds. This finding is consistent with the economic intuition of demand-side frictions in market pricing discussed in Section 2.4 as well: a weakened market demand puts downward pressure on bond prices and raises yields, enlarging the green discount. This result in the same way reinforces prior evidence (Fatica et al., 2021; Febi et al., 2018; Kapraun et al., 2021) that liquidity is not merely a market microstructure feature but a determinant of the cost of capital for sustainable debt instruments. In other words, the reduced liquidity directly makes the cost of capital of the green bond for the issuer more expensive.

- *Sub-hypothesis 1.2: higher Greenwashing is associated with a larger  $GD_{i,t}$ .*

Greenwashing, measured by  $GWScore_{combo}$ , shows a negative but insignificant coefficient of -2.03: a one-unit increase in  $GWScore$  is associated with a 2.03% reduction in the green discount. This relationship contradicts the expectation as it suggests that firms perceived to be engaging in greater greenwashing may already face higher borrowing costs, for the market incorporates skepticism toward superficial ESG claims. Investors may demand higher yields from such issuers to compensate for perceived credibility risks. The lack of significance may partially explain this counterintuition:  $GWScore$  observations are available for only 48% of the bond-level sample (196 out of 408 bonds), which greatly constrains the statistical power. Furthermore, because greenwashing is primarily a firm-level strategic behavior rather than bond-specific, its impact may be less effective at the bond-level, this also motivates treating  $GWScore$  as a dependent variable in *Main Hypothesis 2* and examining which issuer-specific factors influence its intensity.

Among the control variables, CreditRating is statistically significant at 1% ( $p=0.008$ ), this indicates that a one-unit decrease in the numerical credit rating, shown as an improvement in credit quality, is associated with a 0.88% increase in the green discount. In other words, better-rated bonds tend to enjoy more favorable pricing, this is also consistent with investor preference for lower credit risk. Additionally, Coupon is significant at 10% level ( $p=0.0966$ ). Other controls variables, such as coupon rate, maturity, and modified duration, do not exhibit statistically significant relationships with the green discount. Finally, industry and year fixed effects are included to account for sector-specific and temporal influences, but the corresponding dummies are not individually significant, suggesting that variation in the green discount is not strongly driven by industry classification or issuance year within this model.

#### 7.1.2 Robustness Checks for Main Hypothesis 1

- *Alternative Greenwashing Measure -  $GWScore_{sep}$*

To test the robustness of the main findings, the baseline regression is re-estimated using the separated  $GWScore$  ( $GWScore_{sep}$ ) that is derived from the pillar-based ESG score. Because  $GWScore_{sep}$  is constructed without the ESG Controversy scores, it is more general and lenient compared with  $GWScore_{combo}$ . If the estimated relationship between green discount and greenwashing is sensitive to the strictness of the greenwashing definition, then the change of  $GWScore$  measure should alter both the magnitude and statistical significance of the coefficient ( $\alpha_2$ ). Comparing test results across the two specifications helps assess whether the observed association is robust to broader or stricter definitions.

As shown in Column (2) in Table 5, the results are directly consistent with the baseline with reduced statistical power. Only Bid-Ask Spread and Credit Rating remain significant at the 10% level. The coefficient on  $GWScore$  retains statistically insignificant, but the sign has reversed. Although no robust conclusion can be drawn under this looser specification, this change still implies the sensitivity of the estimate to the definition of

greenwashing. The lower explanatory power (adjusted  $R^2$ ) also declines modestly (from 0.092 to 0.117), this is expected given the noisier nature of  $GWScore_{sep}$ .

This robustness check supports the earlier rationale for prioritizing  $GWScore_{combo}$  in the main hypothesis, for its stricter construction (anchored in ESG controversy data) offers a more precise and informative signal of a bond's greenwashing behavior. Moreover, since green discount is not mathematically derived from the ESG score components, concerns about endogeneity resulting from the inclusion of ESG controversies are also mitigated.

- *Clustering effects*

In this regression, a key concern is the potential correlation of residuals within issuers, as many firms in the sample issue multiple green bonds. Such intra-cluster correlation can lead to underestimated standard errors and inflated statistical significance.

In the dataset, multiple green bonds are issued by the same firm. For example, Tesla has issued 58 green bonds, Apple 3, and Citigroup Inc. 10. Bonds from the same issuer are likely to share similar unobserved characteristics such as governance structures, disclosure practices, or ESG strategies. This introduces within-firm correlation in the regression error terms and violates the independence assumption. As a result, it could bias the standard errors downward, inflating t-statistics and potentially increasing the Type I error risk. To address this issue and follow the approach of Flammer (2021), standard errors are clustered at the issuer level to correct for both heteroskedasticity and intra-firm dependence in the residuals. After adjusting for the dependence, the clustered estimation should produce larger and more conservative standard errors and, consequently, weaker statistical significance.

First, the OLS model was re-estimated with robust standard errors. As shown in Column 1, Table 6, under this specification, the bid-ask spread remains positive and statistically significant ( $\alpha = 8.16$ ,  $p = 0.019$ ), consistent with *sub-hypothesis 1.1*. The *GWScore* changes to a negative coefficient ( $\alpha = -2.03$ ) but remains statistically insignificant ( $p = 0.132$ ). Among the control variables, the significance and magnitude of *CreditRating* are unchanged, reinforcing its stable association with green bond pricing. Note also that *Modified duration* is consistently insignificant across specifications, it suggests that the green bond pricing in the sample is not systematically related to interest rate sensitivity. Again, the *GWScore<sub>sep</sub>* (test results in Appendix Table A4) measure shows the same result with reduced power.

Secondly, as shown in Column (2) in Table 6, when adjusting for clustering at the issuer level, the coefficient on bid-ask spread remains virtually unchanged in magnitude, but its statistical significance diminishes and its standard errors increase from 3.420 to 6.384. This change reflects the expected clustering impact: it corrects the downward bias in standard errors and yields more conservative inference; in other words, the standard errors increase because the model accounts for the non-independence of observations within the same firm. Interestingly, *GWScore* becomes statistically significant at the 10% level, this lends support to the view in Section 7.1.1 that greenwashing is primarily a firm-level strategic behavior rather than a bond-specific. Finally, *CreditRating* remains significant in both specifications, robust ( $p = 0.008$ ) and clustered ( $p = 0.065$ ), reinforcing its stable association with green bond pricing.

Additionally, some industry and year fixed effects show statistical significance, such as the Telephone sector and the year 2021. The significance of the Telephone industry dummy is solely driven by the presence of a single issuer: Verizon Communications Inc., it issued 6 green bonds in between 2019 and 2024. Essentially, this result reflects within-firm variation for Verizon, rather than an industry-wide effect. Similarly, the year 2021 becomes statistically significant at the 5% level, this is previously observed in Figure 2

(Section 5.2.1), where 2021 marks the peak in both the number and total value of green bond issuances in the U.S. corporate market. These two fixed effects are consistent with underlying structural patterns in the data; the remaining industry and year dummies appear well-controlled and do not unduly influence the regression estimates.

In conclusion, although the clustering at the issuer level has impacted the estimated standard errors and thus the explanatory powers of certain variables, the directions of the coefficients remain consistent across models. Notably, the emergence of *GWScore* as statistically significant in the clustered regression further motivates the shift to *Main Hypothesis 2*, which examines firm-specific characteristics as potential determinants of greenwashing across issuers.

**Table 6: Robust Regression Results for Main Hypothesis 1**

| Variable        | (1) Robust SE        | (2) Clustered SEs (by Issuer Name) |
|-----------------|----------------------|------------------------------------|
| BidAskSpread    | 8.1633**<br>(3.420)  | 8.1633<br>(6.384)                  |
| GWScore         | -2.0292<br>(1.339)   | -2.0292*<br>(1.215)                |
| Coupon          | 1.0366*<br>(0.619)   | 1.0366<br>(0.923)                  |
| Maturity        | -0.0312<br>(0.450)   | -0.0312<br>(0.319)                 |
| LogFV           | -0.4991<br>(1.01)    | -0.4991<br>(0.726)                 |
| ModDuration     | -0.4416<br>(0.800)   | -0.4416<br>(0.681)                 |
| CreditRating    | -0.8777**<br>(0.325) | -0.8777*<br>(0.476)                |
| Financial       | -1.4142<br>(6.902)   | -1.4142<br>(3.203)                 |
| Industrial      | 1.392<br>(6.783)     | 1.392<br>(2.962)                   |
| Special Purpose | 0.1179<br>(10.531)   | 0.1179<br>(3.568)                  |
| Telephone       | 5.3493<br>(8.339)    | 5.3493*<br>(2.861)                 |
| Trans-Rail      | 0.4046<br>(10.364)   | 0.4046<br>(3.641)                  |
| Utility-Elec    | 1.6091<br>(7.154)    | 1.6091<br>(4.120)                  |
| Utility-Gas     | -1.0135<br>(13.561)  | -1.0135<br>(5.003)                 |
| Y2017           | 8.9952<br>(16.175)   | 8.9952*<br>(4.963)                 |
| Y2018           | 5.4818<br>(16.055)   | 5.4818<br>(6.030)                  |
| Y2019           | 8.5064<br>(11.777)   | 8.5064*<br>(4.623)                 |
| Y2020           | 6.9269<br>(11.596)   | 6.9269<br>(5.297)                  |
| Y2021           | 13.7075<br>(11.504)  | 13.7075**<br>(6.257)               |
| Y2022           | 5.5427<br>(11.675)   | 5.5427<br>(4.656)                  |
| Y2023           | 3.5853<br>(11.598)   | 3.5853<br>(3.749)                  |
| Y2024           | 0.2849<br>(12.121)   | 0.2849<br>(4.646)                  |
| Observations    | 134                  | 134                                |
| R-squared       | 0.263                | 0.263                              |
| Adj. R-squared  | 0.117                | 0.117                              |
| F-statistic     | 1.8                  | -12800000000                       |
| p(F-statistic)  | 0.0249               | 1                                  |

**Note:**

Significance levels are denoted as: \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Robust standard errors are reported in parentheses and re-estimated under a heteroskedasticity-consistent (HC1) estimator.

Table 6. This table reports robust test results for *Main Hypothesis 1*. The key independent variable of interest is  $GWScore_{combo}$ . Column (1) presents results using HC1 standard errors; Column (2) reports standard errors clustered at the issuer level to account for within-firm correlation. Both models include fixed effects for industry and issuance year.

## **7.2 Quantitative Findings for Main Hypothesis 2 and Robustness Checks**

### **7.2.1 Quantitative Findings and Implications**

Column 1 of Table 7 presents the results of the OLS regression analyzing the firm-level determinants of greenwashing behavior.  $GWScore_{sep}$  is used in this level of analysis while  $GWScore_{combo}$  is used for robustness check. The results will again be interpreted individually by sub-hypothesis.

**Table 7: Regression Results of Main Hypothesis 2**

| Variable          | (1) $GWScore_{sep}$   | (2) $GWScore_{combo}$ |
|-------------------|-----------------------|-----------------------|
|                   | -0.0387***<br>(0.013) | 0.0444**<br>(0.019)   |
| CreditRating      | -0.005<br>(0.003)     | -0.0021<br>(0.004)    |
| EScore            | -0.0046<br>(0.004)    | 0.0019<br>(0.006)     |
| SScore            | 0.0045*<br>(0.002)    | -0.0125***<br>(0.003) |
| GScore            | -0.058**<br>(0.026)   | 0.0092***<br>(0.003)  |
| InvestorSentiment | -0.3874***<br>(0.032) | 0.4972***<br>(0.048)  |
| LogFirmSize       | 0.0047<br>(0.013)     | -0.0133<br>(0.020)    |
| Leverage          | 0.0054<br>(0.005)     | -0.0109<br>(0.007)    |
| ROA               | -0.3797<br>(0.267)    | 0.6256<br>(0.407)     |
| Financial         | -0.8403***<br>(0.269) | 1.2323***<br>(0.410)  |
| Industrial        | -0.0963<br>(0.398)    | 0.2171<br>(0.606)     |
| Special Purpose   | -0.6164*<br>(0.313)   | 1.1198**<br>(0.478)   |
| Telephone         | -0.3377<br>(0.391)    | 0.9327<br>(0.596)     |
| Trans-Rail        | -0.466*<br>(0.266)    | 0.5778<br>(0.404)     |
| Utility-Elec      | -0.638<br>(0.500)     | 0.8829<br>(0.763)     |
| Utility-Gas       | -0.6768<br>(0.452)    | 1.5642**<br>(0.681)   |
| Y2016             | -0.7069<br>(0.476)    | 2.1696***<br>(0.704)  |
| Y2017             | -0.2159<br>(0.462)    | 1.8647***<br>(0.695)  |
| Y2018             | -0.3681<br>(0.231)    | 1.4197***<br>(0.319)  |
| Y2019             | -0.2006<br>(0.214)    | 1.2067***<br>(0.293)  |
| Y2020             | -0.2322<br>(0.200)    | 1.0638***<br>(0.261)  |
| Y2021             | -0.1467<br>(0.197)    | 1.0067***<br>(0.269)  |
| Y2022             | -0.5067***<br>(0.185) | 1.9098***<br>(0.259)  |
| Y2023             |                       |                       |
| Observations      | 195                   | 198                   |
| R-squared         | 0.742                 | 0.663                 |
| Adj. R-squared    | 0.707                 | 0.618                 |
| F-statistic       | 21.370                | 14.870                |
| p(F-statistic)    | 0.0000                | 0.0000                |

**Note:**

Significance levels are denoted as: \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .  
Robust standard errors are reported in parentheses.

Table 7. This table reports OLS regression of Sub-hypotheses 2.1 - 2.5. All regressions include industry and year fixed effects (coefficients not reported).

- *Sub-hypothesis 2.1: Firms with lower credit quality (i.e., higher credit risk) are more likely to engage in greenwashing.*

Credit rating is positively and significantly associated with greenwashing behavior ( $t = -3.047$ ,  $p = 0.003$ ), in line with the expectation. Specifically, a one-unit increase in the credit rating score, or a one-unit deterioration in credit quality, is associated with a 0.039% increase in the greenwashing score. This relationship shows its economical meaning too; it suggests that financially weaker firms may have stronger incentives to engage in strategic or symbolic ESG disclosure. Such firms typically face high borrowing costs and greater scrutiny from creditors, by emphasizing sustainability commitments rather than through costly performance improvements, they can reframe investor perception by appealing to ESG-oriented investors to, which can potentially offset the negative risk assessments tied to lower credit quality. In doing so, they may use heightened environmental signaling as a reputational hedge to sustain market access and investor interest.

- *Sub-hypothesis 2.2: Firms with stronger Environmental performance are less likely to greenwash.*

The environmental score (EScore) is negatively associated with greenwashing, though the relationship is not statistically significant ( $t = -1.594$ ,  $p = 0.113$ ). The coefficient sign aligns with the expectation of *sub-hypothesis 2.2* that firms with stronger environmental performance have less incentive to engage in symbolic ESG disclosure. Robust environmental practices can reduce the marginal benefit of overstating sustainability credentials, as the firm can faithfully signal its commitment through verifiable actions. This is consistent with the literature (e.g., Flammer (2021); Löffler et al., (2021)), which emphasizes that genuine environmental performance enhances market trust and reduces the need for reputational “green gloss.”

- *Sub-hypothesis 2.3: Firms with stronger social performance are less likely to greenwash, but to a lesser extent than their Environmental score.*

As expected, the Social Score (SScore) also carries a negative but insignificant coefficient direction as EScore ( $t = -1.248$ ,  $p = 0.058$ ). This aligns with the idea that the social pillar is less directly relevant in the green bond context, which primarily focuses on environmental objectives. As such, the social performance variation appears to have limited explanatory power in predicting greenwashing behavior in this setting.

- *Sub-hypothesis 2.4: Firms with stronger governance scores are more likely to greenwash.*

The Governance Score (GScore) is positively associated with greenwashing and statistically significant at the 10% level ( $t = 1.908$ ,  $p = 0.059$ ): a one-point improvement in governance performance is associated with a 0.45 basis point increase in the greenwashing score. This result suggests that stronger governance may facilitate greenwashing behavior. Firms with a well-developed governance framework typically have better managerial capacity and reporting systems, and greater investor outreach, these capabilities may enable them to construct superficial sustainability narratives that exceed their actual performance. Governance strength becomes a strategic asset that for tailoring reports that specifically appeal to ESG-oriented investors, rather than a constraint on symbolic disclosure. This finding also adds nuance to ESG signaling theory in suggesting that the credibility of sustainability statements depends on both aggregate ESG standing and the relative strength or weakness of its pillars.

- *Sub-hypothesis 2.5: Firms with investor sentiment, e.g., higher Tobin's Q, are less likely to greenwash.*

Consistent with the revised hypothesis, investor sentiment, proxied by Tobin's Q, is negatively and significantly associated with greenwashing behavior ( $t = -2.237$ ,  $p = 0.027$ ).

A one-point increase in Tobin's Q corresponds to a 0.06% reduction in the greenwashing score: firms with higher market valuations, in other words, firms with greater investor trust and confidence, are less likely to engage in symbolic ESG disclosure. Economically, this suggests that investor optimism functions as an informal governance mechanism: trusted firms have less incentive to overstate their sustainability performance, as doing so could jeopardize the credibility that underpins their valuation premium. In essence, when a firm is already regarded favorably by the market, it is more likely to act with integrity, and no external force is likely to induce opportunistic ESG misrepresentation.

Among firm fundamentals, firm size is negatively and significantly related to greenwashing ( $\beta = -0.3874$ ,  $p = 0$ ), suggesting that larger firms are less likely to misrepresent ESG performance, potentially due to greater public scrutiny, stronger reputational incentives, or more established sustainability practices. Other control variables (leverage, ROA, liquidity) are not significant.

It is also notable to see that the Industrial ( $\beta = -0.8385$ ,  $p = 0.012$ ), Telephone ( $\beta = -0.6164$ ,  $p = 0.051$ ), and Utility-Elec ( $\beta = -0.466$ ,  $p = 0.081$ ) sectors exhibit significant variations in greenwashing propensities, this echoes the descriptive patterns shown in Section 5.2.2, where those sectors displayed dispersions in the *GWScore* within industries. Such heterogeneity also reinforces the importance for controlling for both industry-specific practices and time-varying factors in analyzing greenwashing behavior.

In sum, the findings of *Main Hypothesis 2* offer practical implications for issuers. These results show that credit quality, governance profile, and investor sentiment materially influence both market pricing and perceptions of ESG credibility. A drop in credit quality correlates with higher greenwashing scores, as financially weaker firms may use sustainability claims to offset their negative risk perceptions. Similarly, stronger governance may also enable firms with the strategic capability to create sophisticated

disclosures that overtake substantive environmental performance. By contrast, the force of investor sentiment appears to be moderating, with stronger market valuations linked to lower greenwashing, possibly due to greater scrutiny and reputational accountability.

Practically, if issuers intend to reduce the green discount, they should focus on enhancing transparency, securing credible third-party verification, and demonstrating measurable environmental performance. These steps can strengthen investor confidence, narrow bid-ask spreads, and mitigate the credibility risk perception. As the results suggest, price benefits like reputational signaling, brand differentiation, and alignment with long-term sustainability strategy may still justify issuance. Treasurers therefore must either absorb higher underwriting costs for a label that does not lower coupons or invest in stronger verification and project tracking to restore investor trust and potentially boost pricing. For investors, they should not solely rely on the green label, they must vigilantly assess pillar-level ESG performance to avoid being misled by greenwashing. Labels alone are insufficient, meaningful due diligence requires assessing whether the three pillar scores are indeed aligned with disclosed commitments and project outcomes. If failed, they risk paying a “green tax” for bonds that deliver little real impact.

Ultimately, the penalty observed in the form of a green discount signals market frustration with inconsistent standards and fragmented verification practices. This supports the case for tighter disclosure requirements and a standardized ESG taxonomy as well as suggesting that any financing advantage from green bonds in the US will depend on issuers’ ability to combine credible reporting with tangible environmental outcomes.

#### 7.2.2 Robustness Checks for Main Hypothesis 2

- *Alternative Greenwashing Measure -  $GWScore_{combo}$*

Although  $GWScore_{sep}$  is used as the dependent variable to avoid potential endogeneity as a result of the inclusion of ESG Controversies that  $GWScore_{combo}$  carries, the OLS model is still re-estimated using the latter, like the treatment of *Main Hypothesis 1*. Because  $GWScore_{combo}$  is more stringent than  $GWScore_{sep}$ , testing it can help examine whether the test results hold under a stricter definition and if  $GWScore_{sep}$  dilutes the statistical power.

As shown in Column 2, Table 7, using  $GWScore_{combo}$  leads to reversal in sign and significance for several key variables. For example, CreditRating and GScore flips signs ( $\beta = 0.0444$  and  $-0.0125$ , respectively); and InvestorSentiment become significantly positive ( $\beta = 0.0092$ ). This may be because  $GWScore_{combo}$  is embed both cause and consequence, as ESG controversies often arise after poor ESG or financial performance and can trigger reactive disclosure efforts. Similarly, firms with stronger governance capabilities may be better equipped to respond to controversies, thus appearing more engaged in greenwashing under the composite score.

Such unexpected directional shifts in the estimated coefficients seem to suggest that the composite score may embed not only the firm's symbolic ESG behavior but also elements of reputational backlash, regulatory exposure, or other ex-post market reactions. This also reflects a broader concern that  $GWScore_{combo}$  may capture both the cause and the consequence of firm behavior, making it vulnerable to reverse causality. Motivated by this, the next section formally investigates whether greenwashing behavior could be influencing firm-level characteristics, rather than being determined by them, by conducting a series of reverse causality tests.

- *Reverse-causality*

Reverse-causality arises when the dependent variable may influence one or more of the explanatory variables. As mentioned previously, the greenwashing behavior might affect

firm characteristics rather than result from them. For instance, since *GWScore* is mathematically derived from the ESG scores, it is directly dependent on the E, S, and G pillar scores too. If a firm had engaged in greenwashing activity through channels like internal reporting policies, external assurance, or stakeholder pressure, it could alter its future ESG performance or disclosure practices which could mechanically feed back into the same variables used to explain it. Similarly, greenwashing might also temporarily boost investor sentiment, perception of governance quality, or credit risk assessments, if rating agencies factor ESG credibility into their evaluations. If such feedback effects exist, the estimated main regression coefficients will suffer from simultaneity bias and cannot be interpreted causally.

To address this concern, five additional OLS regressions were estimated with a one-year lag. Specifically, the lagged *GWScore* ( $GWScore_{Lag1}$ ) is served as the key independent variable, and the dependent variables were CreditRating, EScore, SScore, GScore, and InvestorSentiment. In this way, the analysis isolates whether prior greenwashing behavior predicts changes in these firm-level characteristics over time.

The results (shown in Table 8) provide strong evidence against reverse causality for most variables. Lagged greenwashing behavior does not significantly predict future changes in credit rating, investor sentiment, or firm fundamentals ( $p > 0.10$  in all cases). These findings suggest that greenwashing is not driven by anticipation of future shifts in those firm-level characteristics; it supports the interpretation of *GWScore* as a contemporaneous strategic behavior, rather than a response to expected improvements or deterioration.

Governance performance (GScore), however, displays a positive and statistically significant relationship with  $GWScore_{Lag1}$  ( $p = 0.0062$ ), it indicates that firms with

higher prior greenwashing scores tend to exhibit approximately 7.73% better governance performance in future periods. This pattern may reflect deliberate managerial efforts to reestablish legitimacy, improve compliance with stakeholder expectations, or mitigate reputational risks following past greenwashing activities. This result shows that greenwashing is integrated in strategic decision-making processes, rather than opportunistic or accidental but embedded.

As a robustness check, the same regression was also estimated using  $GWScore_{combo}$ , which is derived from the ESG Combined Score. Under this specification, EScore exhibits strong statistical significance ( $p = 0.017$ ) compared to the main model using  $GWScore_{sep}$ . This result is expected due to the underlying construction of the variables: the ESG Combined Score inherently includes EScore, and since  $GWScore_{combo}$  is mathematically derived from it, the likelihood of mechanical correlation and thus reverse causality, increases. In particular, the observed significance of EScore likely reflects partial endogeneity, as any change in EScore directly affects both ESG Combined Score and, by extension,  $GWScore_{combo}$ . Similarly, the increased significance of GScore ( $p < 0.01$ ) is consistent with this structural overlap. These patterns reinforce the decision to use  $GWScore_{sep}$  at this level of analysis, because it helps avoid variable construction overlap and potential mechanical bias.

Overall, these tests reinforce the main model's treatment of greenwashing as a behavioral outcome rather than a forward-looking adjustment to ESG or financial conditions. Firms engaging in greenwashing are not merely anticipating changes in their ESG performance, they are rather participating in reputational management shaped by existing incentives, constraints, and disclosure environment

**Table 8: Reverse Causality Result for Main Hypothesis 2**

| <i>GWScore<sub>sep</sub></i>   |                         |                                    |                                  |                                     |                              |
|--------------------------------|-------------------------|------------------------------------|----------------------------------|-------------------------------------|------------------------------|
| Variable                       | (1)<br>Credit<br>Rating | (2) EScore                         | (3) SScore                       | (4) GScore                          | (5)<br>Investor<br>Sentiment |
| GWScore_Lag1                   | 0<br>(0)<br>1***        | -1.1335<br>(3.498)<br>-2.9253***   | -2.5969<br>(2.846)<br>-3.2545*** | 7.7289*<br>(4.093)<br>-4.3542***    | 0<br>(0)<br>0                |
| CreditRating                   | (0)<br>0<br>0***        | (0.52)<br>1.4263<br>10.5567***     | (0.423)<br>2.5697<br>5.8977***   | (0.609)<br>2.8658*<br>11.8252***    | (0)<br>1***<br>0**           |
| InvestorSentiment              | (0)<br>0***             | (1.295)<br>10.5567***              | (1.054)<br>5.8977***             | (1.515)<br>11.8252***               | (0)<br>0**                   |
| LogFirmSize                    | (0)<br>0***             | (1.847)<br>-1.007**                | (1.503)<br>0.4198                | (2.162)<br>1.2321**                 | (0)<br>0                     |
| Leverage                       | (0)                     | (0.502)                            | (0.409)                          | (0.588)                             | (0)                          |
| ROA                            | 0 (0)                   | -0.3867<br>(0.309)                 | -0.3631<br>(0.252)               | -1.2764***<br>(0.362)               | 0<br>(0)                     |
| Observations                   | 119                     | 119                                | 119                              | 119                                 | 119                          |
| R-squared                      | 1                       | 0.775                              | 0.758                            | 0.701                               | 1                            |
| Adj. R-squared                 | 1                       | 0.763                              | 0.745                            | 0.684                               | 1                            |
| <i>GWScore<sub>combo</sub></i> |                         |                                    |                                  |                                     |                              |
| Variable                       | (1)<br>Credit<br>Rating | (2) EScore                         | (3) SScore                       | (4) GScore                          | (5)<br>Investor<br>Sentiment |
| GWScore_Lag1                   | 0***<br>(0)<br>1***     | -5.6575**<br>(2.337)<br>-2.5428*** | -2.3065<br>(1.903)<br>-2.9925*** | -8.0157***<br>(2.717)<br>-4.1576*** | 0<br>(0)<br>0                |
| CreditRating                   | (0)<br>0**              | (0.517)<br>2.6283*                 | (0.421)<br>3.2657***             | (0.601)<br>3.7734**                 | (0)<br>1***                  |
| InvestorSentiment              | (0)<br>0***             | (1.339)<br>14.3466***              | (1.091)<br>8.4277***             | (1.557)<br>13.0546***               | (0)<br>0**                   |
| LogFirmSize                    | (0)<br>0                | (1.633)<br>-1.1161**               | (1.329)<br>0.3651                | (1.898)<br>1.098*                   | (0)<br>0**                   |
| Leverage                       | (0)<br>0***             | (0.512)<br>-0.7573**               | (0.417)<br>-0.5409*              | (0.595)<br>-1.6816***               | (0)<br>0                     |
| ROA                            | (0)                     | (0.346)                            | (0.281)                          | (0.402)                             | (0)                          |
| Observations                   | 120                     | 120                                | 120                              | 120                                 | 120                          |
| R-squared                      | 1                       | 0.766                              | 0.747                            | 0.693                               | 1                            |
| Adj. R-squared                 | 1                       | 0.754                              | 0.734                            | 0.677                               | 1                            |

**Note:**

Significance levels are denoted as: \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Robust standard errors are reported in parentheses.

Table 8. This table reports the results of regressions testing for potential reverse causality for *Main Hypothesis 2*. The lagged *GWScore* (*GWScore<sub>Lag1</sub>*) is included as an explanatory variable for subsequent dependent variables in columns (1) – (5). Industry and year fixed effects are included but not reported

### 7.3 The Matching Principle and Discussion

As outlined in Section 2.3, the matching principle is a common approach for isolating the pricing effect of the green label. In addition to the main WACC-based framework, this matching method is also applied to the sample as a supplementary test to benchmark the results against existing literature, and to assess its practical limitations in the US corporate bond market. This exercise is not intended to discredit the approach but to provide an empirical illustration of how its stringent matching requirements can reduce sample size and statistical power. The following analysis applies the matching criteria to the dataset, allowing for a direct comparison of findings across methodologies.

From the original bond-level sample of 408 green bonds, 120 green bonds from 28 issuers that had issued only green bonds are excluded, because the absence of conventional counterparts made direct comparison impossible. For each remaining green bond, a conventional bond from the same issuer is identified, matched on key characteristics: S&P credit rating, coupon rate (identical or similar), and coupon type. Given the challenge of finding identical maturities, a tolerance window of  $\pm 5$  years on the maturity date and  $\pm 0.5\%$  on the coupon rate are adopted to ensure comparability. All bond characteristics, including coupon structure, maturity, and credit rating, are obtained from Bloomberg. Following the matching procedure, bonds with insufficiently comparable matches are subsequently excluded. In total, 313 green bonds were dropped due to unsuccessful matching, leaving a final sample of 95 perfectly matched pairs from 63 issuers.

Next, the YTM of each green bond is compared against its matched counterpart, and the yield spread is computed as:

$$YTM_{green} - YTM_{conventional} \quad (6)$$

A positive spread indicates the existence of green discounts, whereas the negative spread indicates greenium.

To test whether the average spread exists or not, a paired t-test was applied under the null hypothesis that the mean yield difference equals zero. The rejection of the null would imply a statistically significant pricing differential - either a greenium or green discount, depending on the sign of the estimated mean spread.

**Table 9: Paired-Sample t-Test of the Matching Principle**

| Statistic               | YTM <sub>green</sub> | YTM <sub>conventional</sub> |
|-------------------------|----------------------|-----------------------------|
| Mean                    | 5.17                 | 4.94                        |
| Variance                | 6.77                 | 1.61                        |
| Observations            | 95                   | 95                          |
| Degrees of freedom (df) | 94                   |                             |
| t-statistic             | 0.42                 |                             |
| p-value (two-tailed)    | 1.99                 |                             |

*Table 9.* This table reports the results of a paired-sample t-test comparing the mean YTM of green bonds and their matched conventional counterparts. The null hypothesis is that the mean YTM is zero. The test fails to reject the null hypothesis, indicating that the matched-pair analysis provides no evidence of a systematic or green discount in this sample.

As shown in Table 9, the test produced a t-statistic of 0.42 ( $p = 1.99$ ), it suggests that, within closely matched bond pairs, green bonds are not priced at a discount, but this result lacks statistical and economic relevance. This outcome aligns with prior studies that find no systematic greenium in the US corporate bond market under the matching framework. One likely explanation for this absence of significance lies in the substantial reduction in the sample size: approximately 76% of the observations were excluded during the matching process, this may have considerably diminished the statistical power of the test. This finding also supports the concern raised earlier that the matching principle may lose predictive strength when applied to relatively small or segmented markets, such as the US corporate green bond market.

From the economic perspective, the lack of no meaningful greenium could also be explained by investor sentiment. The investors may perceive little pricing difference between a green and a conventional bond. According to Larcker and Watts (2020) and

Flammer (2021), there is evidence that US investors may not systematically value the green label, especially in the absence of stringent third-party verification. As recent market commentary also shows, US fixed-income buyers no longer grant a meaningful “greenium”: a June-2025 *Financial Times* piece on the rise of “greenhushing” reports that labelled deals now price no cheaper than conventional bonds, with the cost incentive “diminished” as investors balk at paying up for environmental labels (Schmitt, 2025). Similarly, the latest RBC Global ESG Fixed-Income Investor Survey confirms the shift: among 110 institutions managing \$26 trillion, the average greenium investors say they will concede has collapsed to barely one basis point, down from 2022, and many US respondents expect none (RBC Capital Markets, 2024). The matched bonds in the sample may also have been issued during a relatively stable market environment, when ESG pricing frictions and investor sensitivity to green labels were less pronounced. As Flammer (2021) notes, the green bond market, particularly in the US, is still emerging. Thus, the absence of a pricing differential now may not generalize to future years, especially as ESG investor demand and regulatory pressures continue to evolve.

The empirical results hold unique and practical implications for various stakeholder groups in the US corporate green bond market, influencing how issuers, investors, and regulators react on issuance, evaluation, and oversight.

## **8. Limitations**

### **8.1 Data Coverage and Sample Composition**

The scope of this analysis is constrained by data availability, despite the WACC-based framework has already broadened the applicability relative to the matching method. The final dataset comprises of only 408 labelled bonds. Moreover, the limited coverage ESG performance and disclosure scores makes the complete *GWScore* unavailable for calculation for more than half of the issuers, such thin data coverage may bias coefficients toward issuers that report more comprehensively. Additionally, the Bloomberg “Green

Instrument Indicator” relies on issuer self-identification, this may lead to misclassification when third-party verification is absent. For instance, even though the first green bond in the US was officially issued in 2013, the Bloomberg database still includes bonds that were issued as early as 2009, this inconsistency greatly challenges data accuracy. These constraints underscore the importance of improving data coverage, quality, and verification standards in green bond research.

## 8.2 Measurement Limitations

The two formulas (Equations (1) and (2)) used to calculate the dependent variables carry inherent methodological limitations.

Firstly, the green discount formula (Equation (1)) is not precise enough. Although this benchmark is based on the famous WACC framework, it remains model-dependent and relies on assumptions about capital structure and tax rates. It does not explicitly account for bond-specific contractual features like covenants, callability, or embedded options, which may influence pricing independently of green status. Besides, the Bloomberg cost-of-debt series is an estimate, not a traded rate and it may diverge from the marginal price that investors observe. This may create measurement noise.

Similarly, whilst the derivation of  $GWScore_{i,t}$  (Equation (2)) quantitatively captures one dimension of greenwashing, it cannot fully encompass qualitative elements such as misleading use-of-proceeds allocation, selective disclosure, or omission of negative impacts. Even with pillar-level decomposition, some subtle credibility signals perceived by investors may still be overlooked and not quantified.

### **8.3 Temporal scope**

The dataset covers green bonds issued between 2013 and early 2025 as to include post-pandemic times. But it does not address the potential impact of future SEC climate disclosure rules or the evolving International Sustainability Standards Boards (ISSB) or International Financial Reporting Standards (IFRS) sustainability standards. As all these regulatory changes comes to pass, market pricing and greenwashing incentives may change substantially.

## **9. Conclusion**

This thesis set out to investigate whether US corporate green bonds deliver a measurable pricing advantage: “greenium”, and to understand the firm-level characteristics that shape greenwashing behavior. The empirical strategy combines a bond-level analysis of pricing dynamics with a firm-level analysis of ESG disclosure-performance gaps, enabling a richer view of how environmental credibility and market structure interact.

At the bond level, the evidence points to a persistent green discount, rather than a greenium: green bonds are on average issued at yields that is 3.05% above the firm’s estimated financing costs. This effect is not an anomaly but a systematic feature of the current US corporate market, where label credibility is not underpinned by strict certification or verification requirements. Liquidity, captured by the bid-ask spread, is a consistent determinant of the discount, reflecting that market depth is central to the pricing of sustainable debt. The application of a WACC-based benchmark is in place of a conventional matching approach, this expands the analytical reach of green discount testing, accommodating issuers without suitable conventional comparators and aligning yield expectations with firm-specific financing profiles. In contrast, matching-pair tests on a reduced sample of 95 bonds find no yield difference, echoing Flammer (2021) and

Larcker and Watts (2020) and reinforcing the view that any benefit of issuing remains largely reputational rather than financial.

At the firm level, the analysis of greenwashing uncovers structural drivers that transcend individual bond issues. Credit quality, governance capacity, and investor sentiment each exert significant influence on the likelihood and intensity of greenwashing. The patterns observed suggest that financially weaker firms may lean on sustainability messaging as a compensatory signal, while well-governed firms may deploy their organizational sophistication to craft ESG narratives that outpace substantive performance. In contrast, stronger investor sentiment correlates with lowering greenwashing, implying that market trust can serve as an informal yet effective accountability mechanism.

The integration of bond-level and firm-level perspectives constitutes a methodological contribution in itself, bridging the gap between market microstructure analysis and corporate ESG behavior. By extending greenwashing detection to the individual ESG pillar level, the study also refines the diagnostic tools available for assessing sustainability claims, highlighting that environmental, social, and governance dimensions do not contribute equally to credibility risk.

These findings have important implications. For regulators, they should emphasize the urgency of developing standardized disclosure rules, reliable ESG taxonomies, and enforceable penalties for misinformation. They should also address the liquidity gaps through targeted market-making incentives or enhanced secondary-market transparency. For issuers, the results mean that the green label alone likely won't secure lower borrowing costs in the current environment; financing benefits of the green label are more likely when it is supported by transparent verification and measurable project outcomes. For investors, it is necessary to look beyond labels to evaluate true ESG performance, for

protecting portfolios from reputational risk as well as ensuring that the capital drives genuine environmental impact.

Looking ahead, the future path for the US green bond market will likely depend on regulatory interventions, investor sophistication, and evolving global standards. Tightening disclosure standards and verification becomes more rigorous, this may help recover the informative value of the green label, potentially reversing the current pricing disadvantage. Until then, the market will continue to reward transparency and penalize ambiguity - an outcome consistent with the broader lesson of this research: in sustainable finance, credibility is as valuable as capital.

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# Appendix

**Table A1: Selective Bloomberg Terminal Research Result**

| Issuer Name                 | CUSIP     | Issuer Industry | S&P Rating | Cpn  | Coupon Type | YTM (Mid) | Maturity Date | Par Amt | Pricing Date | Bid-Ask Spread (LQA) | Years to Maturity (from today) | 6. Mod Dur (Mid) | Amt Issued (in \$M) |
|-----------------------------|-----------|-----------------|------------|------|-------------|-----------|---------------|---------|--------------|----------------------|--------------------------------|------------------|---------------------|
| Boston Properties LP        | 10112RBH6 | FINANCIAL       | BBB        | 6.50 | FIXED       | 5.6981    | 2034-01-15    | 1000    | 2021-03-02   | 0.43                 | 8.89                           | 6.57             | 750                 |
| Dana Inc                    | 235825AH9 | INDUSTRIAL      | BB-        | 4.25 | FIXED       | 5.5125    | 2030-09-01    | 1000    | 2021-04-29   | 1.00                 | 5.49                           | 4.79             | 400                 |
| Ford Motor Co               | 345370DB3 | INDUSTRIAL      | BBB-       | 6.10 | FIXED       | 6.2099    | 2032-08-19    | 1000    | 2022-08-16   | 0.45                 | 7.46                           | 5.89             | 1,750               |
| General Motors Co           | 37045VAY6 | INDUSTRIAL      | BBB        | 5.40 | FIXED       | 5.1485    | 2029-10-15    | 1000    | 2022-07-28   | 0.38                 | 4.61                           | 3.83             | 1,000               |
| Intel Corp                  | 458140CA6 | INDUSTRIAL      | BBB        | 4.15 | FIXED       | 5.4775    | 2032-08-05    | 1000    | 2022-08-02   | 0.55                 | 7.27                           | 6.06             | 1,250               |
| JPMorgan Chase Bank NA      | YR8515342 | BANK            |            | 5.78 | FIXED       | 5.8504    | 2030-03-04    | 252     | 2025-02-07   | 0.61                 | 4.98                           | 4.21             | 13                  |
| MidAmerican Energy Co       | 595620AZ8 | UTILITY - ELEC  | A          | 5.30 | FIXED       | 5.7083    | 2055-02-01    | 1000    | 2019-01-07   | 1.38                 | 29.89                          | 14.38            | 600                 |
| MP Materials Corp           | 553368AA9 | INDUSTRIAL      |            | 0.25 | FIXED       | 3.5279    | 2026-04-01    | 1000    | 2021-03-24   | 0.58                 | 1.05                           | 1.03             | 690                 |
| NSTAR Electric Co           | 67021CAN7 | UTILITY - ELEC  | A-         | 3.25 | FIXED       | 4.7823    | 2029-05-15    | 1000    | 2022-09-12   | 0.60                 | 4.18                           | 3.79             | 400                 |
| Prologis LP                 | 74340XBT7 | FINANCIAL       | A          | 4.63 | FIXED       | 5.0421    | 2033-01-15    | 1000    | 2020-08-06   | 0.30                 | 7.84                           | 6.43             | 650                 |
| PVH Corp                    | 693656AD2 | INDUSTRIAL      | BBB-       | 4.13 | FIXED       | 3.7753    | 2029-07-16    | 1064    | 2024-04-09   | 0.37                 | 4.34                           | 3.80             | 558                 |
| Realty Income Corp          | 756109BB9 | FINANCIAL       | A-         | 1.13 | FIXED       | 4.9735    | 2027-07-13    | 1384    | 2021-07-08   | 0.25                 | 2.33                           | 2.18             | 554                 |
| Tesla Energy Operations Inc | 83417KFS2 | INDUSTRIAL      |            | 5.45 | FIXED       | 6.8597    | 2031-01-14    | 1000    | 2016-01-11   |                      | 5.84                           | 4.84             | 5                   |
| Verizon Communications Inc  | 92343VGW8 | TELEPHONE       | BBB+       | 5.50 | FIXED       | 5.7217    | 2054-02-23    | 1000    | 2019-02-05   | 0.70                 | 28.95                          | 14.12            | 1,000               |
| VF Corp                     | 918204AX6 | INDUSTRIAL      | BB         | 0.25 | FIXED       | 4.4175    | 2028-02-25    | 1088    | 2023-02-23   | 0.64                 | 2.95                           | 2.81             | 544                 |
| Walmart Inc                 | 931142ET6 | INDUSTRIAL      | AA         | 1.80 | FIXED       | 4.4607    | 2031-09-22    | 1000    | 2021-09-08   | 0.34                 | 6.52                           | 5.94             | 2,000               |
| Welltower OP LLC            | 95040QAK0 | FINANCIAL       | BBB+       | 2.70 | FIXED       | 4.5717    | 2027-02-15    | 1000    | 2019-12-09   | 0.24                 | 1.92                           | 1.83             | 500                 |

*Table A1.* This table reports bond-level characteristics for selective U.S. corporate green bonds in the sample. All values are sourced from Bloomberg and expressed in U.S. dollars where applicable.

**Table A2: S&P Credit ratings in numerical values**

| <b>Rating</b> | <b>Score</b> | <b>Description</b>                                             |
|---------------|--------------|----------------------------------------------------------------|
| AAA           | 1            | Extremely strong capacity to meet obligations                  |
| AA+           | 2            | Very strong, slightly lower than AAA                           |
| AA            | 3            | Very strong                                                    |
| AA-           | 4            | Very strong, but some susceptibility                           |
| A+            | 5            | Strong, but more vulnerable to economic conditions             |
| A             | 6            | Strong                                                         |
| A-            | 7            | Strong, but more affected by environment                       |
| BBB+          | 8            | Adequate capacity, lowest upper-tier investment grade          |
| BBB           | 9            | Adequate capacity                                              |
| BBB-          | 10           | Adequate capacity, lowest investment grade                     |
| BB+           | 11           | Less vulnerable in the near term but faces uncertainties       |
| BB            | 12           | Faces major ongoing uncertainties                              |
| BB-           | 13           | Speculative, financial instability                             |
| B+            | 14           | More vulnerable but still has the capacity to meet obligations |
| B             | 15           | Highly speculative                                             |
| B-            | 16           | Greater vulnerability                                          |
| #N/A          | 16           | #N/A                                                           |

*Source: Adapted from S&P Global (n.d.) and the numerical convention used by the National Association of Insurance Commissioners. (NAIC, 2013).*

*Table A2.* This table presents the conversion of S&P corporate credit ratings into numerical scores. Higher ratings correspond to lower scores, indicating stronger credit quality, while lower ratings correspond to higher scores, reflecting weaker creditworthiness. Unrated bonds or those with missing values are assigned the maximum score of 16.

**Table A3: Sample of Calculated *GWScore* Values**

| <b>Issuer Name</b>                  | <b>Ticker</b>              | <b>Issuer Industry</b> | <b>Year</b> | <b><i>GWScore<sub>combo</sub></i></b> | <b><i>GWScore<sub>sep</sub></i></b> |
|-------------------------------------|----------------------------|------------------------|-------------|---------------------------------------|-------------------------------------|
| AES Corp/The                        | AES US Equity              | UTILITY - ELEC         | 2020        | 0.6122                                | 0.4022                              |
| Alexandria Real Estate Equities Inc | ARE US Equity              | FINANCIAL              | 2019        | -1.6348                               | 0.3896                              |
| Ameren Illinois Co                  | AEE US Equity              | UTILITY - ELEC         | 2021        | 1.4232                                | 0.4756                              |
| Citigroup Inc                       | C US Equity<br>CMCSA US    | FINANCIAL              | 2022        | 0.9930                                | -1.8617                             |
| Comcast Corp                        | Equity                     | INDUSTRIAL             | 2023        | 1.1982                                | -0.7739                             |
| Dana Inc                            | DAN US Equity              | INDUSTRIAL             | 2021        | 0.6840                                | 0.4531                              |
| Dominion Energy Inc                 | D US Equity                | UTILITY - ELEC         | 2021        | 0.1287                                | -0.0284                             |
| Duke Energy Carolinas LLC           | DUK US Equity              | UTILITY - ELEC         | 2018        | 1.7690                                | -0.2827                             |
| Eastman Chemical Co                 | EMN US Equity              | INDUSTRIAL             | 2023        | -0.0107                               | 0.3898                              |
| Enphase Energy Inc                  | ENPH US Equity             | FINANCIAL              | 2021        | -0.1761                               | 0.4615                              |
| Enphase Energy Inc                  | ENPH US Equity             | FINANCIAL              | 2021        | -0.1761                               | 0.4615                              |
| Entergy Louisiana LLC               | ETR US Equity              | INDUSTRIAL             | 2022        | 1.3265                                | 0.4580                              |
| Equinix Inc                         | EQIX US Equity             | FINANCIAL              | 2022        | 0.4197                                | 0.4399                              |
| Federal Realty OP LP                | FRT US Equity              | FINANCIAL              | 2020        | -1.0840                               | 0.3787                              |
| Federal Realty OP LP                | FRT US Equity              | FINANCIAL              | 2023        | -0.6117                               | 0.3738                              |
| Fifth Third Bancorp                 | FITB US Equity<br>FSRNQ US | BANK                   | 2021        | -0.5568                               | 0.3886                              |
| Fisker Inc                          | Equity                     | INDUSTRIAL             | 2021        | 0.0721                                | 0.5099                              |
| Ford Motor Co                       | F US Equity                | INDUSTRIAL             | 2022        | 2.0988                                | -1.3248                             |

*Table A3.* This table reports selective issuer-level greenwashing scores of U.S. corporate green bond issuers. Positive values indicate higher levels of greenwashing, whereas negative values reflect alignment between ESG disclosure and performance.

**Table A4: Robust Regression Results for Main Hypothesis 1 (with  $GWScore_{sep}$ )**

| Variable        | (1) Robust SE | (2) Clustered Ses (by Issuer Name) |
|-----------------|---------------|------------------------------------|
|                 | 5.5068*       | 5.5068                             |
| BidAskSpread    | (3.231)       | (4.835)                            |
|                 | 1.3605        | 1.3605                             |
| GWScore         | (1.289)       | (0.841)                            |
|                 | 1.0181        | 1.0181                             |
| Coupon          | (0.62)        | (0.881)                            |
|                 | -0.0345       | -0.0345                            |
| Maturity        | (0.461)       | (0.318)                            |
|                 | -0.2843       | -0.2843                            |
| LogFV           | (1.097)       | (0.683)                            |
|                 | -0.4096       | -0.4096                            |
| ModDuration     | (0.815)       | (0.66)                             |
|                 | -0.7776*      | -0.7776*                           |
| CreditRating    | (0.313)       | (0.452)                            |
|                 | -0.3701       | -0.3701                            |
| Financial       | (6.972)       | (2.361)                            |
|                 | 1.2278        | 1.2278                             |
| Industrial      | (6.92)        | (2.438)                            |
|                 | 1.7763        | 1.7763                             |
| Special Purpose | (10.604)      | (2.944)                            |
|                 | 5.8535        | 5.8535**                           |
| Telephone       | (8.472)       | (2.49)                             |
|                 | -0.061        | -0.061                             |
| Trans-Rail      | (10.613)      | (3.503)                            |
|                 | 1.0862        | 1.0862                             |
| Utility-Elec    | (7.351)       | (3.999)                            |
|                 | 0.3437        | 0.3437                             |
| Utility-Gas     | (13.8)        | (4.049)                            |
|                 | 7.0065        | 7.0065*                            |
| Y2017           | (16.232)      | (4.091)                            |
|                 | 1.9399        | 1.9399                             |
| Y2018           | (15.894)      | (4.078)                            |
|                 | 6.5101        | 6.5101*                            |
| Y2019           | (11.812)      | (3.917)                            |
|                 | 5.0905        | 5.0905                             |
| Y2020           | (11.634)      | (4.814)                            |
|                 | 11.4882       | 11.4882**                          |
| Y2021           | (11.46)       | (5.136)                            |
|                 | 3.4115        | 3.4115                             |
| Y2022           | (11.586)      | (3.868)                            |
|                 | 1.406         | 1.406                              |
| Y2023           | (11.533)      | (3.554)                            |
|                 | -1.6804       | -1.6804                            |
| Y2024           | (12.212)      | (4.468)                            |
| Observations    | 134           | 134                                |
| R-squared       | 0.242         | 0.242                              |
| Adj. R-squared  | 0.092         | 0.092                              |
| F-statistic     | 1.163         | 1.163                              |
| p(F-statistic)  | 0.0556        | 0.0556                             |

**Note:**

Significance levels are denoted as: \* for  $p < 0.1$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Robust standard errors are reported in parentheses and re-estimated under a heteroskedasticity-consistent (HC1) estimator.

Table A4. This table reports robust test results for Main Hypothesis 1. The key independent variable of interest is  $GWScore_{sep}$ . Column (1) presents results using HC1 standard errors; Column (2) reports standard errors clustered at the issuer level to account for within-firm correlation. Both models include fixed effects for industry and issuance year.